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INSTRUMENTS FOR VISUALIZATION OF SELF, CO, AND SOCIALLY SHARED REGULATION OF LEARNING USING MULTIMODAL ANALYTICS: A SYSTEMATIC REVIEW

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Abstract

This thesis presents a systematic literature review in the intersection of multimodal learning analytics, regulation theories of learning, and visual analytics literature of the last decade (2011- 2021). This review is to collect existing research-based instruments designed to visualize Self-Regulation of Learning (SRL), Co-Regulation of learning (CoRL), and Socially Shared Regulation of learning (SSRL) using dashboards and multimodal data. The inclusion and exclusion criteria used in this review addressed two main aims. First, to distil settings, instruments, constructs, and audiences. Second, to identify visualization used for targets (i.e., cognition, motivation, and emotion), phases (i.e., forethought, performance, and reflection), and types of regulation (i.e., SRL, CoRL, and SSRL). By following the Preferred Reporting Items for Systematic Reviews and MetaAnalyses (PRISMA) guidelines, this thesis included 23 peer-reviewed articles out of 383 articles retrieved from 5 different databases searched in April 2021. The main findings from this literature review are (a) the included articles used theoretical grounding of SRL in all articles while CoRL is used only in 3 articles and SSRL only in 2 articles; (b) most articles used both teachers and students as the audience for visual feedback and operated in online learning settings; (c) selected articles focused mainly on visualizing cognition and motivation (17 articles each) as targets of regulation, while emotion as the target was applied only in 6 articles; (d) The performance phase was common to most of the articles and used various visualizations followed by reflection and forethought phases respectively. Simple visualizations, i.e., progress bar chart, line chart, color coding, are used more frequently than bubble chart, stacked column chart, funnel chart, heat maps, and Sankey diagram. Most of the dashboard instruments identified in the review are still improving their designs. Therefore, the results of this review should be put into the context of future studies to be utilized by researchers and teachers in recognizing the missing targets and phases of SRL, CoRL, and SSRL in visualized feedback. Addressing these could also assist them in giving timely feedback on students' learning strategies to improve their regulatory skills.

Keywords: Multimodal Learning Analytics, Visual analytics, Self-Regulated learning (SRL), Socially Shared Regulation of Learning (SSRL), Co-Regulation of Learning (CoRL)

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Rohit Mishra

List of Abbreviations and Symbols

SRL	Self Regulated Learning
CoRL	Co-Regulation of Learning
SSRL	Socially Shared Regulation of Learning
PRISMA	Preferred Reporting Items for Systematic Reviews and MetaAnalyses
VA	Visual Analytics
MMLA	Multimodal Learning Analytics
LMS	Learning Management System
LDA	Learning Dashboards
EWS	Early Warning System
EDA	Electrodermal activity
HRV	Heart rate variability
EWS	Early Warning System
AU	Action Units
SoLAR	Society for Learning Analytics Research
AIED	Artificial Intelligence in Education
EDM	Educational Data Mining
LAK	Learning Analytics and Knowledges
SPIDER	Sample, Phenomenon of Interest, Design, Evaluation, and Research
UTOS	Unit, Treatment, Outcome, and Settings
VIT	Visual Inspection Tool
HIMATT	Highly Integrated Model Assessment Technology and Tools
HOWARD	Helping Other with Augmentation and Reasoning Dashboard
UMAP	User Modelling, Adaptation and Personalization
AEQ	Achievement emotions questionnaire
PAUSe	Perceived Affect Utility-Scale
MSLQ	Motivated Strategies for Learning Questionnaire
PALS	The Patterns of Adaptive Learning Study
LASSI	Learning and Strategies Study Inventory
ERQ	Emotion Regulation Questionnaire
AEQ	Achievement emotions questionnaire
PAUSe	Perceived Affect Utility-Scale

1. Introduction

As the earth has made more than 365 rotations since the COVID-19 outbreak announced by World Health Organization[1], it is time to ask whether we are ready to support the learning of 1.2 billion students of 143 countries[2] who are out of schools? This situation caused dizzying disorientation for both teachers and students and forced them to adapt to the premature arrival of future digital education. This disruption calls for change in our understanding of supporting students' learning by providing continuous feedback on their learning strategies. The available digital infrastructure supporting remote learning in the current pandemic situation allows us to observe and analyze the trace of learnings left behind. Such traces shed light upon the socio-cognitive theory of learning (Bandura, 2001; Zimmerman and Schunk, 2011), where cognition, social and emotional aspects of learning are intertwined (Järvelä, 2016). Support for such active, constructive and invisible complex mental process of learning requires timely feedback on students' learning strategies. Such feedback requires visualization of learning to help researchers reveal the complex interaction of the invisible mental and metacognitive learning process (Malmberg, Järvelä, and Järvenoja, 2017).

Visualization of learning helps reveal this complex interaction of the invisible mental processes (Malmberg et al., 2019). However, students' motivation, emotions, and mental regulatory processes are challenging to capture continuously and unobtrusively with traditional educational research methods. D'Mello (2017) suggest focusing on more data channels than the traditional education research offers for understanding different layers of data about learners' individual metacognitive and shared social processes. To address this, Learning Analytics communities are now using multimodal data both from physical and digital spaces (Cukurova, Giannakos, and Martinez-Maldonado, 2020). For example, log file data, eye tracking, facial recognition, and physiological data to get a more holistic picture of the learning (Schneider, 2018). Furthermore, Noroozi et al. (2020), in their recent systematic review on capturing cognitive, motivational, and emotional learning processes using multimodal data, call

[1] https://www.who.int/news/item/29-06-2020-covidtimeline
[2] https://en.unesco.org/covid19/educationresponse

researchers to use both physical and digital data to triangulate subjective and objective data. They argue that triangulation of data could give us a holistic picture of learning processes by providing a more comprehensive view of the phenomenon of multiple learning processes.

It is important to note here that providing such multimodal data to learners can limit their agency and add extraneous cognitive load (Kirschner, 2018). Also, multimodal data analysis is equally intertwined with models and theories (Winne, 2019). Wise (2015) argues that large multimodal datasets could comfortably give us statistically significant patterns. Therefore, she argues that interpreting meaningful patterns based on educational theories and expert knowledge is more important than ever. Complex learning processes need explanation in the form of logical derivations, preferably from established learning theories. Well-established theories and evidence-based understanding help produce tools, which shape an evolving science by structuring the search for meaningful data points (Shannon, 1948). Therefore, theory-informed feedback given to students on their learning strategies is desirable and essential for improving students' regulatory skills. These points direct us to the theory of Self-Regulated Learning (SRL), which provides us with an ongoing process rather than a single snapshot in time (Roll, 2015). Matcha (2020) pointed that SRL theory is a primary focus of learning dashboard designs. In addition, to understand evenly and unevenly distributed social regulations in collaborative learning, Panadero (2015) point that we must explore Socially Shared Regulation of Learning (SSRL) and Co-Regulation of Learning (CoRL), respectively. SSRL involves an interdependent or collectively shared regulatory process when group members are engaged in shared regulation (Järvelä, 2013). CoRL comes from sociocultural learning theories and identifies how learner mediates their cognitions, motivations, and emotions during social interaction between individual and context (Winne, 2010).

Vieira, Parsons, and Byrd (2018), in their recent systematic literature review on Visual Learning Analytics, pointed out the lack of theoretical grounding used in current dashboards and called for interdisciplinary work between information visualization experts and educational researchers. Matcha (2020) found that Learning Analytics Dashboards are rarely grounded in learning theories and thus, fail to support metacognition and do not offer effective learning strategies to students. Here, we also need to consider some critical technical challenges (i.e., manual efforts for data synchronization, sample rate matching, and Signal-to-noise ratio) using multimodal data (Sharma and Giannakos, 2020). Therefore, the objective of this review is to take a systematic approach for collecting existing research-based instruments designed to visualize Self, Co, and Socially Shared Regulation of learning using multimodal data at the level of details previously unexplored. This review will help teachers and researchers give real-time feedback on students' learning strategies to improve students' regulatory skills.

Below are four sub-sections. The first sub-section provided a theoretical conceptualization of individual and group level regulation of learning research by briefly discussing SRL, CoRL, and SSRL. The second sub-section explored multimodal data types, and sources used to track the regulation of learning. The third subsection described the added value of multimodal data in capturing and visualizing regulation of learning based on recent reviews. Finally, the fourth subsection presented the importance and challenges of the triangulation of multimodal data.

1.1. Theoretical Conceptualization of Individual and Group Level Regulation

1.1.1. Self-Regulation of Learning: Individual Level

This review primarily focuses on the Self-Regulated Learning (SRL) model, following a socio-cognitive view that involves three classes of influence on self-regulated behavior: personal, behavioral, and environmental (Zimmerman, 1990, 2002). Winne (2019) defines SRL as a process through which learners monitor and regulate their accessed content and the operations, which they applied for pursuing goals to augment and edit prior knowledge. Zimmerman (2002) defines it as a cyclical process involving three main phases (forethought, performance, and reflection) targeting learners' motivation, emotion, and cognition. The starting phase forethought focuses on understanding the learning task, goal settings, and strategic planning. In the performance phase, learners adapt their behaviors to attain their plans and goals by monitoring their learning processes (Zimmerman, 2002). In the reflection phase, students self-evaluate their strategies and adapt changes to solve future learning challenges (Cleary, 2012; Winne, 2010).

In SRL, three targets, cognitive, motivational, and emotional, are interrelated (Zimmerman, 2002). The cognitive target explores learners' strategic actions and knowledge, for example, retrieval, elaboration, and structuring to remember new knowledge (Pintrich, 1990). Motivation target covers markers for students' learning desire. Finally, emotions can also be the target of regulation. It plays a vital role in executive cognitive functioning, including working memory, inhibitory control, and mental flexibility (Boekaerts and Pekrun, 2015; Winne, 2018).

1.1.2. Socially Shared and Co-Regulation of Learning: Group Level

This review also includes Socially Shared Regulation of Learning (SSRL) and Co-Regulation (CoRL) models to address evenly and unevenly distributed social regulation, respectively (Panadero, 2015). SSRL involves an interdependent or collectively shared regulatory process when group members are engaged in shared regulation (Järvelä, 2013). CoRL comes from sociocultural learning theories and identifies how learner mediates their cognitions, motivations, and emotions during social interaction with an individual (or others) in the environment (Winne, 2010) of learning. In both CoRL and SSRL, individuals share regulations. In CoRL one or more group members guides the regulation of individual learner and SSRL involves group members' reciprocal engagement in regulatory activities (Bransen, Govaerts, Panadero, Sluijsmans, and Driessen, 2021).

According to Järvelä (2018), Self-regulation (regulating oneself), co-regulation (supporting each other), and socially shared regulation (regulating together) jointly create a relatively regulated learning space for individuals working in a group. This regulated learning space in the collaborative group is multifaceted, where learners regulate their motivation, emotions, cognition, and behavior while contributing to the groups' shared regulatory processes. Therefore, studying regulation to provide timely feedback on students' learning strategies needs process data, identifying regulation (inter)actions and individual's interpretation of learning situation. It is needed because when students' skills and knowledge do not meet the requirements of the learning situations, their learning progress becomes jeopardized (Koivuniemi, 2017).

1.2. Multimodal Data Types and Sources

Advanced educational instruments using digital technologies provide researchers micro-level environmental interactions concerning learners' bodily and metacognitive actions (Reimann, 2014). Kraut (2002) describe affordances of these instruments in a digital environment where things are audible, visible, tangible (i.e., touch or clicks), presence-related (i.e., social presence), temporal, reviewable, and revisable. Currently, researchers are using various modalities of data both from physical and digital spaces, i.e., the use of log file data, eye tracking, facial recognition, and physiological data. Such data points can help track student behaviors, e.g., what they do, see, and feel during learning and interaction. Azevedo et al. (2017), with a conceptual framework, and Noroozi et al. (2020), with a systematic review, presented multiple data sources for visualizing individual and groups' cognitive, emotional, meta-cognitive, motivational along with phases, and targets of regulations. Figure 1 presented such multimodal data types and sources to explain the complex interplay of different targets and phases of regulation processes. Azevedo (2015) has divided these multimodal data types into process data (continuous monitoring), self-report data (Questionnaires/surveys), and knowledge Construction data (student products, i.e., blogs, learning diaries).

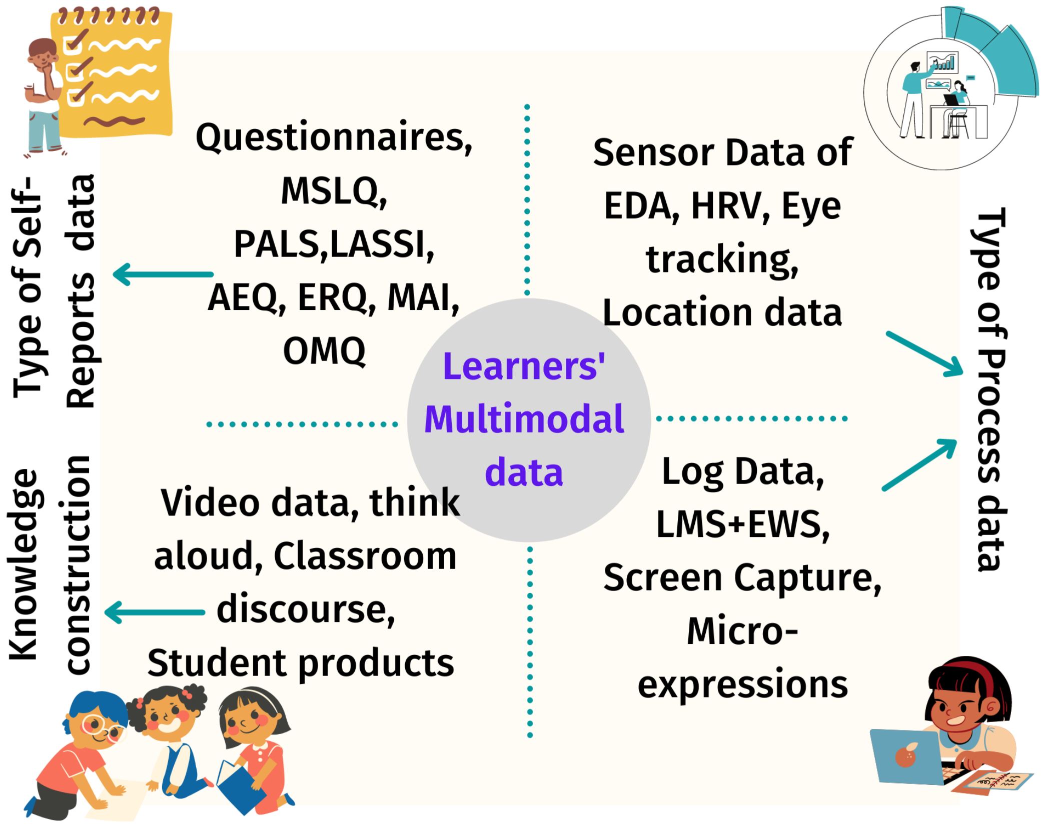

Figure 1.

Multimodal data types and sources use to examine regulation processes

The sources for process data types could be:

- Log data from Learning Management Systems (LMS) provide us with learning traces to follow learning events at micro levels without interrupting learners (Malmberg, 2013).
- The data coming from screen recording (video and audio) provide researchers an opportunity to code and identify verbal and nonverbal expressions of learners (Azevedo and Strain, 2011).
- Eye-tracking data provide identification for a repeated number of fixations on areas of interest by focusing on overall gaze behavior (Taub and Azevedo, 2016).
- Facial expressions or micro-expressions using action units provide evidence scores of learner-centered emotions (e.g., frustration, confusion, boredom) (Munshi et al., 2020).

- Schneider, Börner, Rosmalen, and Specht (2015) listed 82 prototype sensors, i.e., physiological sensors providing skin conductance responses, electrodermal activity (EDA), and heart rate variability (HRV) to capture physiological and behavioral manifestations of learners. These could help see learners' emotions, gaze, cognitive states, and bodily responses and traits, which we cannot see by the naked human eye (Cukurova et al., 2020).

The sources for Self-report questionnaires/ surveys could be:

- For providing evidence regarding students' self-perceptions of several cognitive, meta-cognitive, affective, and motivational beliefs across contexts, i.e., Motivated Strategies for Learning Questionnaire (MSLQ) (Pintrich, 1993), The Patterns of Adaptive Learning Study (PALS) (Midgley, 2014), and The Learning and Strategies Study Inventory (LASSI).
- For providing focus exclusively on one set of processes, for example, Achievement emotions questionnaire (AEQ), on achievement emotions, Emotional Valence (EV) for perceptions of current emotions, Emotion Regulation Questionnaire (ERQ) (Gross and John, 2003) for perceptions of ability to cognitively reappraise and suppress expressions, Perceived Affect Utility-Scale (PAUSe) for perceptions of the utility of affect and emotions, and AEQ, for perceptions of academic achievement emotions.

The source for knowledge construction data could be:

- Concurrent think-aloud data verbalizes self-reports of emotions during learning, problem-solving, and students' performance.
- Student product, i.e., reflection, dairies, blogs.
- Performance measures (Pre/Post-test results).

1.3. Added Value of Multimodal Data in Capturing and Visualizing Regulation of Learning

Multimodal data include linguistic, behavioral, embodied, spatial, visual, and physiological aspects of learning (Jewitt, 2013; Mangaroska, Martinez-Maldonado, Vesin, and Gašević, 2021). It provides possibilities to capture and visualize multifaceted constructs of learning for students and teachers. For example, Dindar, Jarvela, Ahola, Huang, and Zhao (2020) gathered data from different modalities of group interactions to explain the complex interplay of cognitive, motivational, and emotional processes during learning. Such multimodal data usage adds value to the traditional approach to measuring the regulation learning based on data, i.e., self-reports, subjective coding of videos, and verbal protocol. Mitri (2019) pointed out how multimodal data can expose psychomotor skills training, dialogic learning, and co-located group interactions that remain untraceable in learner computer interactions, focused on clicks, keystrokes, or nested software logs. In addition, the use of wearable sensors in learning is on the increase, Schneider et al. (2015) have listed 82 prototypes of such sensors use in learning science research. Such technology allows researchers to move from an event-focused view of learning and explore the descriptive account of events using multimodal data, which provide micro-level environmental interactions about cognitive and non-cognitive learning processes (Noroozi et al., 2019).

By adding data, i.e., log data, physiological measurements, and eye-tracking, provide direct objective information about students' behavioral and mental processes and give valuable insights into the interactions between cognitive and social learning processes. Furthermore, these different data sets allow researchers to triangulate their claims, thus making the evidence concrete (Järvelä, Malmberg, Haataja, Sobocinski, and Kirschner, 2019). For example, researchers have used physiological measures such as tracing skin reactivity changes during challenging learning moments, i.e., emotional arousal (PijeiraDíaz, Drachsler, Järvelä, and Kirschner, 2016). At the same time, video data reveals the sequential and temporal processes of regulatory learning, i.e., planning, cognitive or emotional challenge (Malmberg et al., 2017). Such video data could explain the observed physiological data. These process data-sets address the under-explored potential of assessment data by focusing on an integral part of the learning cycle than considering assessment as an outcome to be optimized (Saqr, 2017).

Methodologically, video data provide observation for social constructs to identify motivation and emotions during learning from a socio-cultural perspective. This video data could complement interviews or self-reports from a socio-cognitive perspective (Järvelä, Volet, and Järvenoja, 2010). Järvelä et al. (2010) illustrate in their study how each data source could capture both individuals as self-regulating agents (cognitive angle) and social processes that provide students' engagement in the activity (situative angle) to study motivation. Furthermore, Cukurova et al. (2020) point the importance of finding a balance between two critical methodological notions: high data quality and low ecologically valid lab studies and low data quality and high ecologically valid in-the-wild studies. This balance is essential for bridging the gap between data quality and ecological validation to use the full potential of MMLA. Therefore, combining multimodal data sources can expose contradictions, ambiguities, and paradoxes, while providing a comprehensive view on the phenomenon of learning (Ercikan and Roth, 2006) while bridging the cognitive-situative divide, which a single data approach could never do.

1.4. Triangulation of Multimodal Data

Data triangulation aims to provide time, space, and personal data for a comprehensive and multi-perspective understanding of the phenomenon investigated (Veronica, 2001, p. 253). In Learning Science research, triangulation involves matching process data resulting from different channels based on the timestamped information related to each data source (Järvelä, 2016). For example, Azevedo and Gašević (2019); Cukurova et al. (2020); Järvelä, Malmberg, Haataja, Sobocinski, and Kirschner (2021); Mu, Cui, and Huang (2020); Noroozi et al. (2020) points out that data triangulation in multimodal research can bring in more accurate predictions about the learning processes compare to single-channel data. The triangulation of many data sources is essential to maximize the inferences made regarding the complex engagement during learning processes

(Azevedo, 2015). In line with this, Noroozi et al. (2020) classified 18 data modalities investigating cognitive, motivational, and emotional processes and highlighted the need to triangulate the objective and subjective data.

A systematic review by Mu et al. (2020) points out three types of relationships at the interaction of multimodal data and learning indicators. First is, *one-to-one*, for measuring one learning indicator, such as measuring cognition using interviews and self-reported questionnaires to increase measurement accuracy. The second is that *many-to-one* identifies multiple data types to measure the same learning indicators, such as measuring learners' engagement using different physiological measures and thus, provide rich information about learning. The third is *one-to-many*, which points to one type of data measure to identify several learning indicators. For example, eye movement data could give us insights into attention, cognition, emotions, collaboration, and engagement and thus provide empirical evidence for data fusion and triangulation.

Thus, multimodal data from different channels could help researchers reveal the complex interaction of the invisible mental and metacognitive learning process (Malmberg et al., 2017). According to Schneider (2018), this kind of holistic picture of learning processes is required compared to the current form of knowledge extracted through individual data sources, for example, log data alone. In such conditions, triangulation of data can help the researchers identify essential learning features and solve several current methodological limitations (Järvelä et al., 2019).

2. Rationale: Tracking and Visualization of Regulated Learning

The introduction section points to the growing interest and its reasoning about using multimodal learning analytics to understand the complex regulatory process. Figure 2 shows multiple reviews at the intersection of regulation theories and multimodal learning analytics (Järvelä et al., 2019; Sharma and Giannakos, 2020; Viberg, Khalil, and Baars, 2020), the intersection of multimodal analytics and visual analytics (Matcha, 2020; Mu et al., 2020; Vieira et al., 2018) and the intersection of regulation theories and visual analytics (Azevedo et al., 2017; Jivet et al., 2021; Noroozi et al., 2020). These studies have synthesized many empirical studies towards a common goal of providing theory-informed feedback to learners. These studies have provided a background for this thesis, which is in the intersection of multimodal learning analytics, regulation theories of learning, and visual analytics.

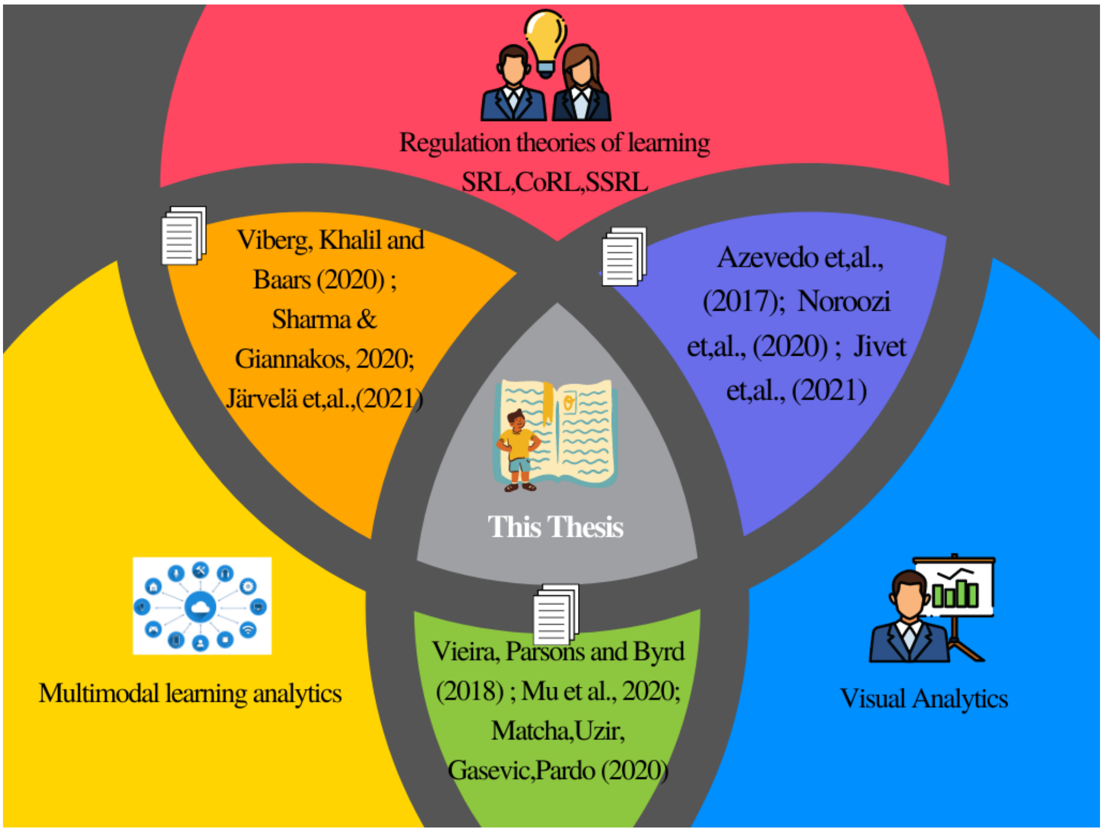

Figure 2.

Schematic of this systematic literature review

2.1. Recent Reviews on Importance of Learning Theories in Researching Learning as a Process

Learning Analytics communities such as Society for Learning Analytics Research (SoLAR), Artificial Intelligence in Education (AIED), Educational Data Mining (EDM), and User Modelling, Adaptation and Personalization (UMAP) all have examples of research that utilizes computationally processed multimodal data (Cukurova et al., 2020). Such studies may include combining data such as self-reports (revealing the intentions of learning) and automatic facial expression (providing behavioral and mental processes like confusion, increasing effort, or increased attention) (Henriques, 2013). The physiological reactions of learners can also be informative data for signaling and measuring regulation mechanisms during the learning process (PijeiraDíaz et al., 2016). With the aid of advanced technologies, signal processing, and machine learning, we are on the verge of "seeing" these complex phenomena and understanding how they interact (Järvelä, Gašević, Seppänen, Pechenizkiy, and Kirschner, 2020). This great potential can offer a new form of transhumanist technologies that can enable students and instructors to perceive meaningful insights that can augment their learning and teaching capacities (Eisenberg, 2017). Here, the use of multivariant graphical displays for multimodal data visualization is quite frequent. However, it ignores the idea of ’perceptual consumption’ (Grinstein and Laskowski, 1998, p. 505), in which loss of information occurs on each layer of visualization. This loss of data complicates the real-time visualization of learning. The problem here is that analyzing data is equally intertwined with models and theories (Winne, 2019). This problem further makes the visualization contextual and thus limited in scope.

Moreover, it is to note that different research units working towards the same goal of visualizing complex learning processes may consider different research paradigms. A research paradigm is a set of beliefs, values, and assumptions that the members of the research community share. A research paradigm plays a vital role in the theoretical coherence and methodological properties of undertaken research. It defines what can count as information to be visualized and to conceptualize the phenomenon under study. Therefore, it is required to extend the methodological paradigm using innovative tools and techniques from educational data mining, machine learning, and affective computing in SRL, CoRL, and SSRL to visualize learning (Baker, 2014). In addition to these all-methodological challenges, there are some critical technical challenges listed below:

- Each data stream has different sampling rates, such as eye-tracking 60–250 Hz, EEG 120–500 Hz, Video 10–60 FPS, Audio 44.1 KHz, heart rate 4 Hz, and thus, processing to ensure that they have the exact temporal resolution.
- All the data streams require synchronization before their corresponding analysis (Ochoa, 2018).
- All data streams carry a different set of noise sources which complicates signal-to-noise-ratio for each data stream. Adjusting similar levels might be a tedious task (Sharma, Giannakos, and Dillenbourg, 2020).
- As per the affordance of the used device, each data stream uses a distinct type of features and measures, therefore, complicates the holistic understanding of learning. For example, emotions from faces (D'Mello, 2017); attention from eye-tracking (Mangaroska, 2018); mental workload from EEG (Doppelmayr, 1998).
- Finally, the most pressing challenge is Learning Analytics specific guidelines (Giannakos, 2019), which require custom-developed scripts and manual data alignment. This manual data alignment is challenging for those who do not have the necessary technical competence.

Researchers working with the Visual Analytics (VA) community have tried to address these problems in the last few years by exploring new visualization techniques to identify relevant information in complex data learning data. (Thomas, 2006, p. 4) define VA as "the science of analytical reasoning facilitated by interactive visual interfaces." It integrates data analysis, visual representations, and user interaction and thus provides technical aid to support human insight (Thomas, 2006). Noroozi et al. (2019) have demonstrated how multimodal data can be combined and visualized regulation processes through the SLAM project, which aims to make visible complex learning processes and develop adaptive regulation. However, a systematic literature review on Visual Learning Analytics by Vieira et al. (2018) explains VA as a computational tool that requires human participation and thus calls for interdisciplinary work between information visualization experts and educational researchers, which seems to be missing.

It is important to remember that the aim of visualization of learning or its logical explanation is not to give a final or absolute answer to how people learn? Its aim should be to create an intellectual track where learners can identify their regulatory processes and eventually internalize these dashboard instruments as their regulation strategies. For example, Martinez-Maldonado, Echeverria, Nieto, and Shum (2020) have used data storytelling in the design of the MMLA visual interface to enable students and teachers to gain insights from the complex data sets. Here the contextualization of multimodal data is essential, without which it is impossible to understand or further investigate how it relates to the regulation of learning (Järvenoja, 2015). Sedrakyan, Malmberg, Verbert, Järvelä, and Kirschner (2020) pointed out that available dashboards mainly target performance visualization, which addresses questions such as, “How do I perform?” They suggest the need for process-oriented feedback, so we can address the question “How can I do better?” Such feedbacks could help students in identifying faults in their learning strategies.

3. Aims and Review Questions (RQs)

The aims of the review were: First, to distill settings, instruments, constructs, and audiences; second, to identify visualization used for targets (i.e., cognition, motivation, and emotion), phases (i.e., forethought, performance, and reflection), and types of regulation (i.e., SRL, CoRL, and SSRL). To address these aims, I designed review questions as per Sample, Phenomenon of Interest, Design, Evaluation, and Research (SPIDER) method developed by Cooke, Smith, and Booth (2012). SPIDER helps search the qualitative and mixed methods research studies along with quantitative research. Figure 3 shows secondary review questions addressing this review's aims.

RQ1: What are the existing instruments, audiences, settings, and constructs used in visualizing SRL, Co-RL, and SSRL for individual and group feedback, respectively?

Description: This question aims to provide a descriptive overview of selected studies. I intend to identify types of dashboard instruments, audience/target groups, where and how of data collection, and constructs used in the visual feedback.

RQ 2: What types of visualization and multimodal data sources existing literature use to visualize different phases, targets, and types of regulation?

Description: This question will highlight the visualization of different phases, types, and targets of regulation used in selected studies. In addition, this question allows identifying data modalities used for extracting information about phase and targets of SRL, Co-RL, and SSRL.

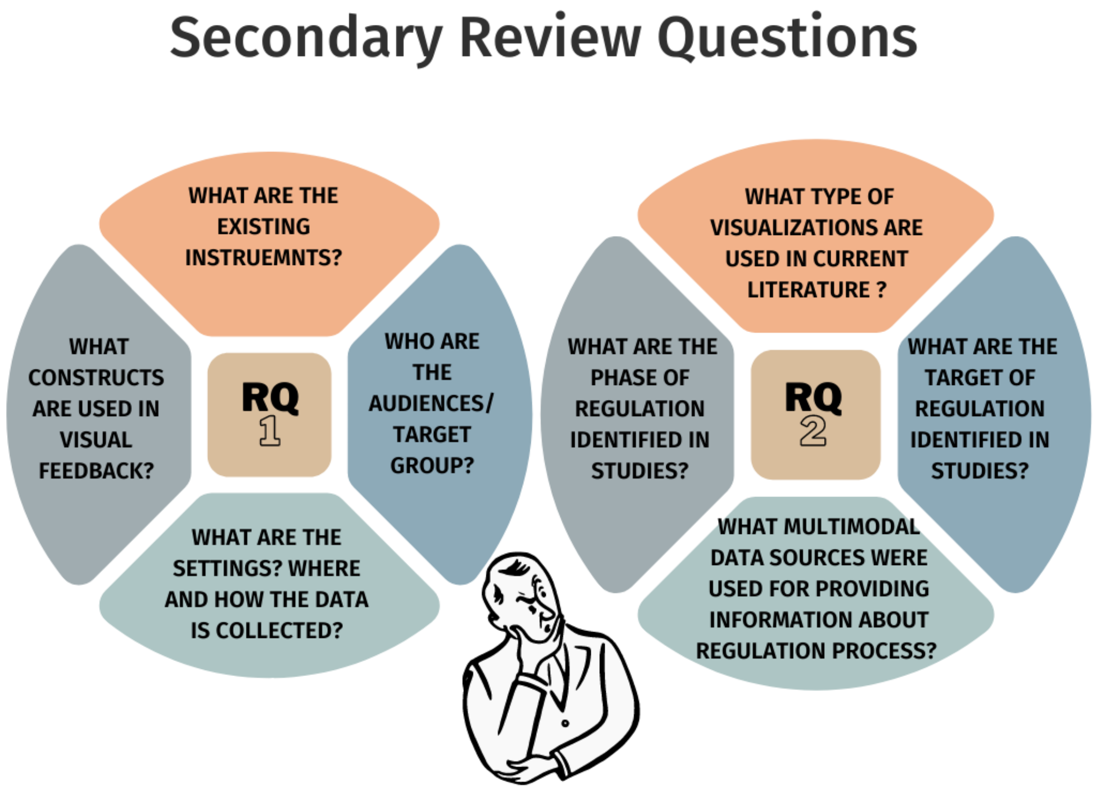

Figure 3.

Secondary Review Questions

4. Methodology

To perform this systematic literature review, I assembled and described a set of peer-reviewed empirical studies, including those using quantitative, qualitative, and mixed methods, which met predetermined criteria (Gough, 2015). The review process can be grouped into three main stages as shown in Figure 4. These stages followed a five-step review methodology elaborated by K. S. Khan, Kunz, Kleijnen, and Antes (2003): 1) frame question for the review, 2) identify relevant studies, 3) assess the quality of identified work, 4) summarize the evidence, and 5) interpret the findings. Publications were selected from 2011-2021, considering tremendous advances during this period with the emergence of the Learning Analytics community. I used Systematic review management software Covidence[3]. The search strings have their first part focusing on detecting regulation theories, the second part identifies tools, and the third part identifies the visualized context. Search for these terms took place in the full text and metadata in 5 critical databases as per their logical conjunctions.

[3] https://www.covidence.org/

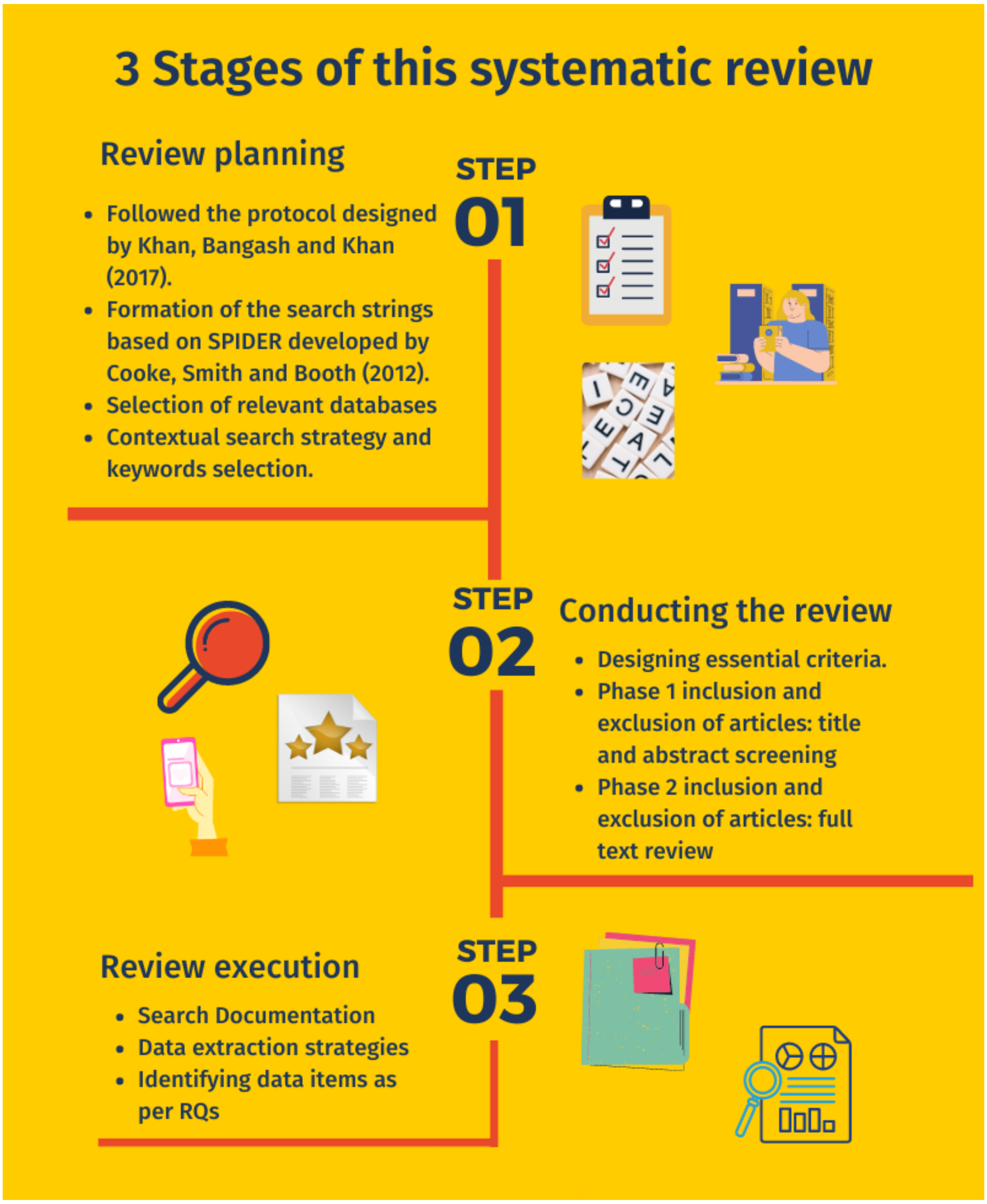

Figure 4.

Overall methodological process and steps taken in this review.

4.1. Review Planning

I followed the protocol designed by S. U. Khan, Bangash, and Khan (2017) for learning analytics with its applications and challenges in the context of big data. Further, I formulated the search strings based on Unit, Treatment, Outcome, and Settings (UTOS) framework relevant to my research questions. Based on search strategy, with the help of the University of Oulu library information experts, we finalized relevant databases below covering peer-reviewed articles from journal and conference proceedings.

4.1.1. Database Selection / Information Sources

A comprehensive search of peer-reviewed articles took place in April 2021. The search included various databases covering Learning Science, Learning Analytics, Technology Enhanced Learning, and Visual Analytics research fields. The search is done in Full text and metadata to avoid missing any relevant article.

- Assembly of Computer Machineries [ACM] Digital Library: It covers conference proceedings of Learning Analytics and Knowledge (LAK), International Conference on Multimodal Interaction (ICMI) along proceedings of ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies.
- Digital Library IEEE explore: It covers proceedings from Artificial Intelligence in Education (AIED), Education Data Mining (EDM) and wide set of IEEE papers.
- ERIC (Educational Resources Information Center) + Academic Search Ultimate: The ERIC (Educational Resources Information Center) database is sponsored by the U.S. Department of Education to provide extensive access to educational-related literature
- SCOPUS: Multidisciplinary abstract and citation database: journals, conference papers.

- Web of Science (WoS): Multidisciplinary abstract and citation database: journals, conference papers

4.1.2. Search Strategy

I have used Cronbach's UTOS framework: Unit, Treatments, Outcome and Setting of study design in Table 1.

Table 1.

Adequacy of the UTOS framework for designing the search strategy

Aspect	Meaning	Scope
Units	The population of interest	Formal education setting, Multi-Modal Learning Analytics
Treatments	The intervention of interest	Target interventions were those explicitly aimed to visualize self, co and socially shared regulatory processes to support learners with their individual and group learning.
Outcomes	What you want to do?	The outcomes of interest in the review are research-based instruments designed for supporting student's self, co and socially shared regulatory skills
Settings	Study Designs	Participatory research; design research; implementation; qualitative and quantitative research, experimental studies

4.1.3. Keywords' Selection and Search String Design

While designing the search string, synonyms of keywords, abbreviations, different ways of writing/spellings, and truncation along with broad and narrow terms have been checked carefully as shown in Table 2. The search string used truncation (*), phrases (""), Boolean operators (AND/OR), and proximity operators (w/2, N/2, NEAR 2). The proximity operators are used to search for close words to each other, but not necessarily next to each other. I used truncation for regulat* for getting results for regulation, regulated and regulate, I also used truncation for visual* for getting results for visualization/visualisation, visual and visualize/visualise. Also, proximity operators such as w/2 NEAR 2 or N/2 between regulat* and learning allowed finding search results for; Regulation of Learning, Regulated Learning. Further, the abbreviation of Multimodal Learning Analytics is used as MMLA. Considering the different ways of writing about visual feedback, I used 'dashboard' as an extra keyword in the search string.

4.1.4. Search Strings Used in Selected Databases

The search strings design focuses on detecting regulation theories; the second part identifies the population of interest, multimodal learning analytics; and the third part identifies the visualized context, outcome, and setting. I adjusted the search string if required for different databases as shown in Table 3.

Table 2.

Terms extracted from the search strategy for search string design

Context	Keywords
Regulation theories	"Self-Regulated learning", "Self-Regulation of learning", "Co-Regulation of Learning", "Socially-Shared Regulation of Learning", "Socially shared Regulated Learning", SRL, CoRL, CRL, SSRL
Multimodal learning analytics	"Learning Analytics", "Multimodal Learning Analytics", "Multi-modal Learning Analytics", MMLA
Visual Analytics	Visualization, Visualisation, Dashboards, Visual analytics

Table 3.

Search string used in selected databases

Database (2011-2021)	Search string in full text and metadata	Number of Articles
Assembly of Computer Machineries [ACM] Digital Library (covers LAK, CHI, ICMI, TEEM, MEDES, UMAP)	(regulat* w/2 learning) AND ("learning analytics" OR "multi modal" OR mmla OR Multimodal) AND (visual* OR dashboard)	107
IEEE explore (covers AIED, EDM, IEEE papers)	(regulat* NEAR/2 learning) AND (visual* OR dashboard) AND ("learning analytics" OR "multi modal")	52
ERIC (Educational Resources Information Center) + Academic Search Ultimate	(regulat* w/2 learning) AND ("learning analytics" OR "multi modal" OR mmla OR Multimoda) AND (visual* Or dashboard)	28
Scopus (Covering British Journal of Education Technology)	(regulat* w/2 learning) AND ("learning analytics" OR "multi modal" OR mmla OR Multimoda) AND (visual* Or dashboard)	137
Web of Science	(regulat* NEAR/2 learning) AND ("learning analytics" OR "multi modal" OR mmla OR Multimodal) AND (visual* OR dashboard)	22

4.2. Conducting the Review / Eligibility Criteria

The review used two phases of inclusion and exclusion criteria based on review questions to select relevant research articles closely related to research questions. In the first phase, I completed the title and abstract screening, and the second phase involved the full-text screening of the selected articles. The Covidence systematic review application has been used for saving these criteria and displayed them alongside the search results, which allowed easy referencing while screening in both phases. The inclusion and exclusion of articles followed the below-mentioned conditions in Figure 5.

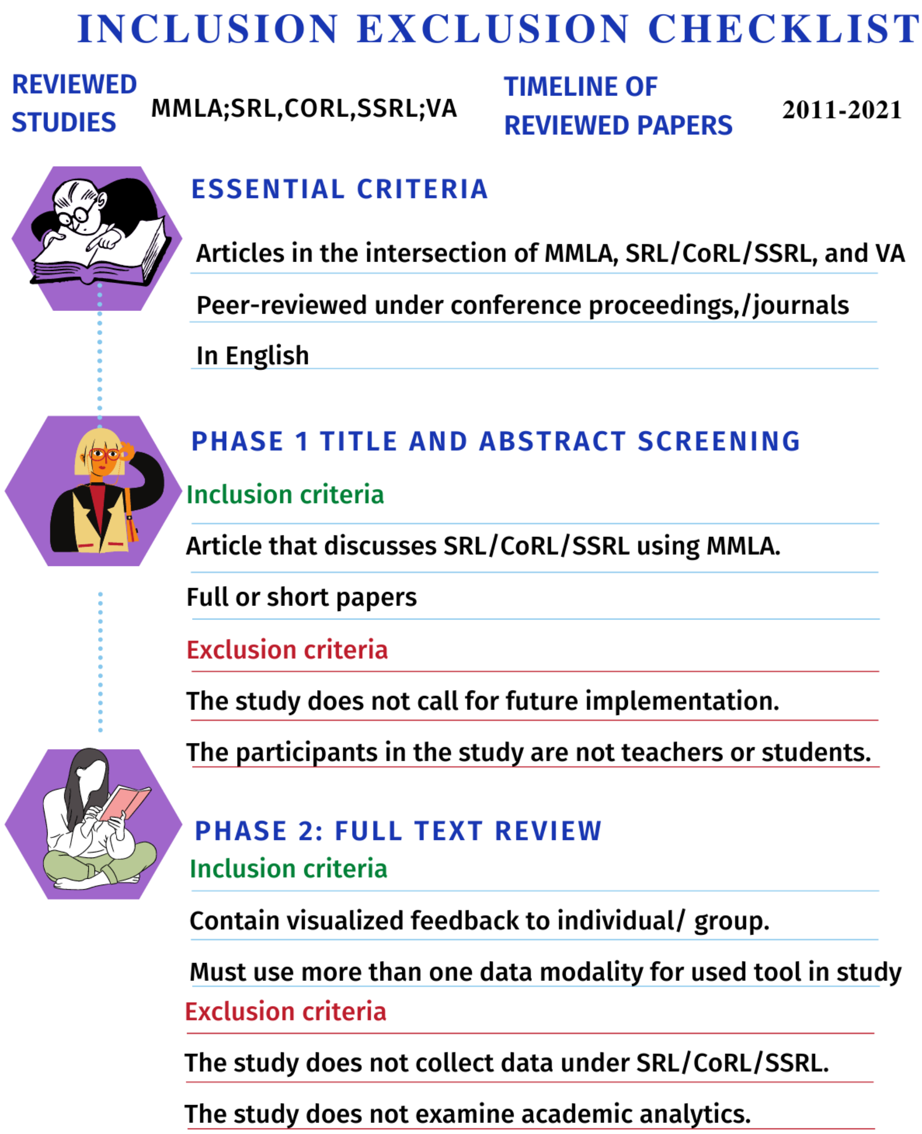

Figure 5.

Inclusion and exclusion criteria used in the review.

I choose the timeline of the last decade (2011-2021), considering the advances in the field of Learning Analytics since 2011. Studies such as posters of preliminary work and symposium sessions are excluded. Studies having participants other than teachers, students and researchers are excluded to avoid papers, which use visuals or dashboards using multimodal data for regulatory behavior, for example, car dashboards, traffic monitoring, or health monitoring dashboards. The examining some form of classroom practice, i.e., academic analytics (macro-level analysis of learning) are excluded to focus on microlearning processes of regulation of learning. Further, I excluded studies that do not specify data collection methods under the theoretical framework of SRL/CoRL/SSRL to focus on the review questions. Finally, I checked that selected studies meet the criteria for rigorous quantitative or qualitative research in learning analytics recommended by Ferguson (2014) to ensure ethical use of learning data.

4.3. Review Execution / Selection Process

4.3.1. Search Documentation

For the search documentation, I used the Covidence software. It allows importing references from different databases using EndNote XML format, the PubMed format, and the RIS text format. The primary search was done in November 2020 and repeated in April 2021 to add new references to selected articles. For the ACM database, I first extracted the Bibtex file to RefWorks[4]. It is needed because from ACM database does not provide compatible file formats of extracted studies for Covidence. To import the reference to RefWorks, I selected BibTex in the search box from the list of importing references. After importing the files in Refwork, I extracted the RIS file and imported it to the Covidence. For other selected databases, the RIS file or EndNote XML format is imported directly to Covidence. After importing all these references, Covidence automatically removes the duplicates, which I cross-checked for verification. After this, Covidence provides the options of title and abstract screening and full-text review. As a final step, Covidence provides options for data extraction strategy.

[4] `https://www.refworks.com/`

4.3.2. Data Extraction Strategy: Coding of Data Items

In this coding phase of the protocol, 12 different variables Appendix1 address the need for research questions as shown in Table 4. The scope of analysis firstly addressed the study overview, i.e., name of the author, study title, year of publication, and later addressed the two RQs.

Table 4.

Data extraction form for selected articles

#	Study Data	Description	Relevance
1	Authors, Study Title and Year	_	Study Overview
2	Dashboard instrument	What are the existing instruments used in visualizing and/or measuring SRL, Co-RL, SSRL?	RQ1
3	Audiences	Who are the audiences/ target groups of multimodal learning analytics?	RQ1
4	Settings	What are the existing settings of where and how the data has been collected?	RQ1
5	Constructs	What constructs are used in the visual feedback provided for students and teachers?	RQ1
6	Regulation Targets	Cognition, Motivation and Emotions	RQ2
7	Regulation Phases	Performance, Forethought and Reflection	RQ2
8	Regulation Types	SRL, CoRL and SSRL	RQ2
9	Visualization Methods	What type of visualizations are used in current literature for different phases and targets of SRL, CoRL, and SSRL?	RQ2
10	Data Sources	What multimodal data sources were used for providing information about different targets, phase and types of regulation?	RQ2

5. Results

5.1. Study Selection

This section presents the results of the search completed in chosen databases and this review's selection process. Out of 383 records identified in the 6-database search resulting in 23 studies in the review, the below PRISMA flow diagram in Figure 6 shows the process in 4 stages: identification, screening, eligibility with the reasoning for excluded and included articles. In the first stage, after removing duplicates total of 346 records were screened in 2 phases: title and abstract screening and full-text screening. Going through the exclusion and inclusion criteria discussed in the method section, the exclusion of 245 records took place. A total of 101 studies followed the second phase for full-text screening. In this phase, the main exclusion criteria were theoretical grounding in Self, Co, and Socially Shared Regulation theories, the use of multimodal data, and visualization for feedback. For this, the method, analysis, and result sections of the selected papers were explored for checking inclusion and exclusion criteria. Finally, 23 studies were identified listed in Table 7 (appendix 1) at the intersection of Regulation theories (SRL/SSRL/CoRL) of learning, multimodal analytics, and visualization using dashboards. This relatively small number is not surprising given that multimodal learning analytics is still in its infancy. Also, researchers have repeatedly pointed out the need for theoretically grounded research in multimodal learning analytics.

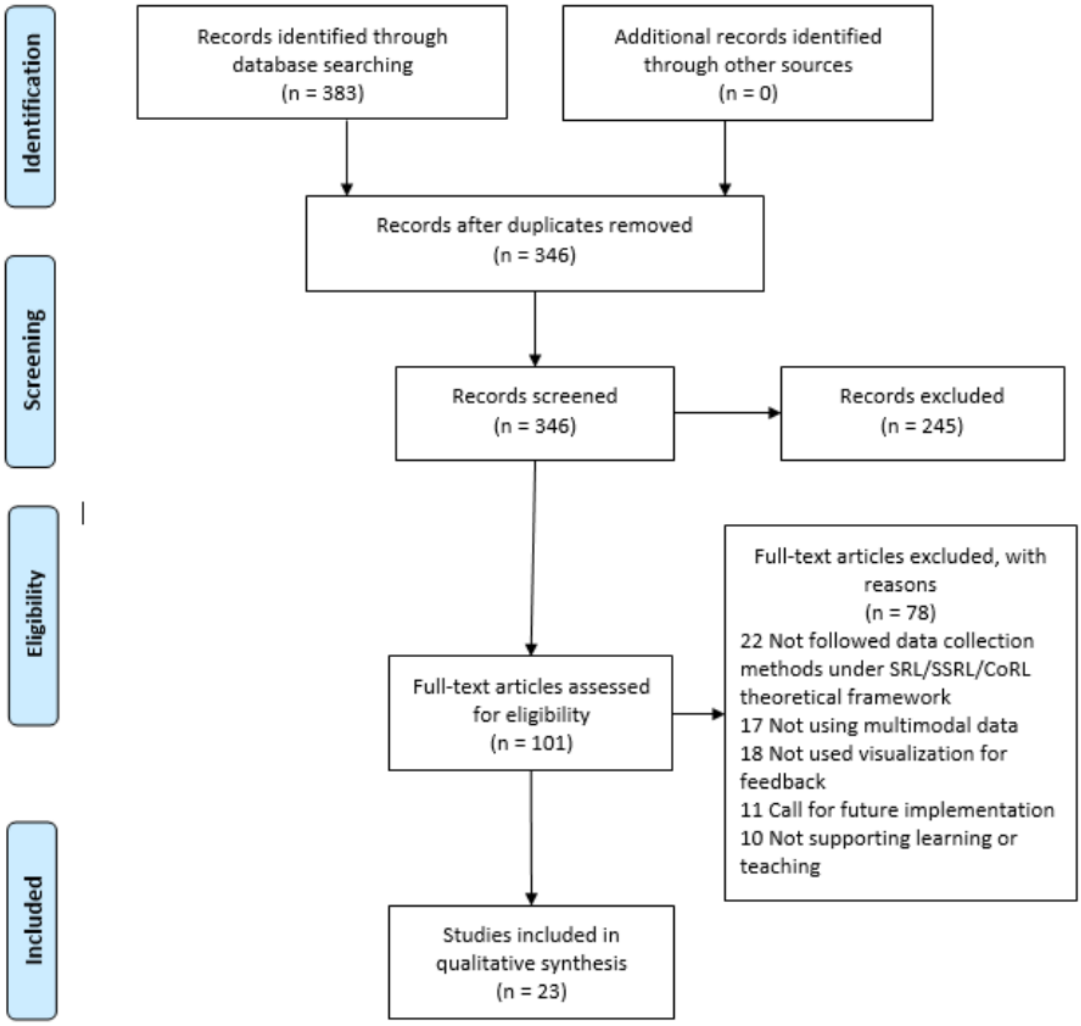

Figure 6.

Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) flowchart (Moher, 2009).

5.2. Overview of the Articles in Systematic Literature Review

Most articles (n=19/23) included in this review came in the last five years (2017-2021), which shows the growing literature in multimodal learning analytics grounded in regulation theories of learning. In Figure 7, we can see that studies included in the review are coming in the last seven years from 2015-2021. shows the distribution of these studies from different countries and learning settings, for example, online, offline, and blended. Nevertheless, as other recent literature reviews have pointed, most of the studies included in this review were also conducted in higher education settings (n=20) only three studies (Malmberg et al., 2019; PijeiraDíaz et al., 2016; Tan, Koh, Jonathan, and Yang, 2017) focus on high school students. Multiple subjects have been covered in terms of subjects and the discipline of participants involved in these studies. Computer Science students are on top, followed by teacher training cohorts, psychology students, and high school science students with problem-based learning.

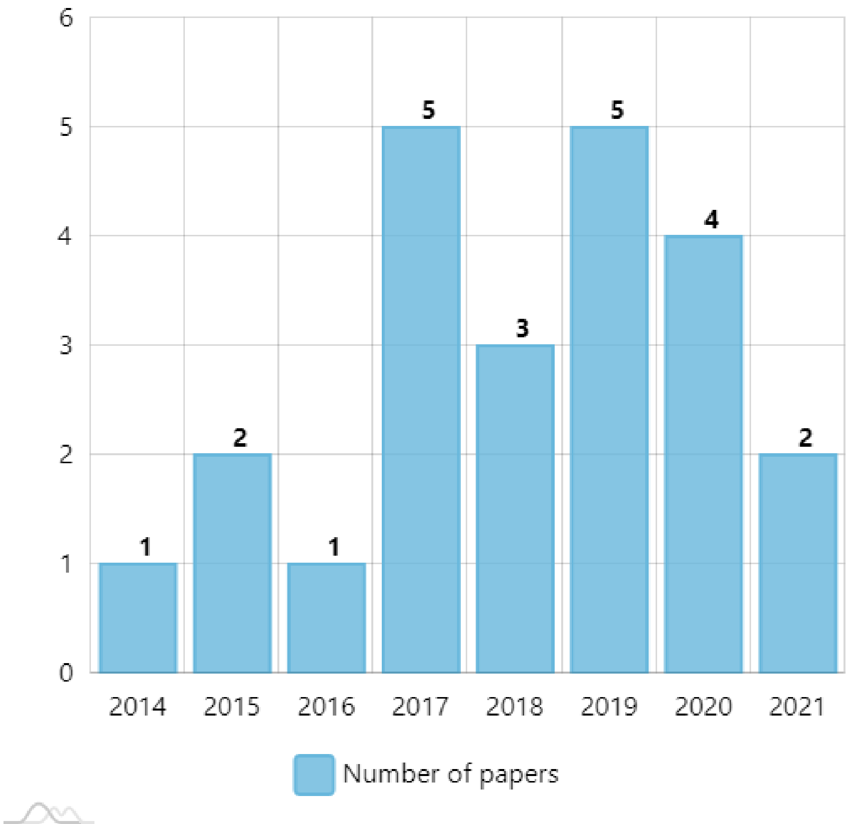

Figure 7.

Overview of the articles of multimodal learning analytics grounded in regulation theories of learning during the years 2014-2021.

5.3. Addressing the Primary and Secondary Review Questions

Based on Table 5, I have addressed the RQ1 and RQ2 in the following six subsections. Here first four subsections addressed RQ1, and the last two subsections addressed RQ2. I used a timeline graph to visualize instruments designed over the last seven years and a pictorial graph to show instruments used by the percentage of studies included in the review. Further, I used stacked column charts to visualize the audiences and contexts; funnel chart to visualize the constructs used in the selected studies. Further, in the fifth and sixth sub-sections, I identified the visualizations and data sources used in selected literature. I have used the Sankey diagram to show the visualizations used in selected literature and the pictorial diagram to show multimodal data types used to identify different phases and targets of regulations.

Table 5.

Secondary review questions and their results in subsection

Review Questions	Secondary Review Question	Results in Subsection
RQ1: What are the existing instruments, audiences, settings, and constructs used in visualizing SRL, Co-RL, and SSRL for individual and group feedback respectively?	What are the existing instruments used in visualizing and/or measuring SRL, Co-RL, SSRL?	5.3.1
	Who are the audiences/ target groups of multimodal learning analytics?	5.3.2
	What are the existing settings of where and how the data has been collected?	5.3.3
	What constructs are used in the visual feedback provided for students and teachers?	5.3.4
RQ 2: What are the types of visualization and multimodal data sources existing literature use to visualize different phases, targets and types of regulation?	What type of visualizations are used in current literature for different phases and targets of SRL, CoRL, and SSRL?	5.3.5
	What multimodal data sources were used for providing information about different targets, phase and types of regulation?	5.3.6

5.3.1. What Are the Existing Instruments Used in Visualizing And/or Measuring SRL, Co-RL, SSRL?

Figure 8 visualize identified dashboard instruments out of the selected articles. In this review, I came across 13 unique dashboards designed to support Self, Co, and Socially Shared Regulation of Learning (Table 6) out of 23 articles included in the review. Figure 9 shows the timeline of these dashboards. Other 11 articles included in the review either presented results to inform dashboard designs (Li et al., 2017; Manso-Vazquez, Caeiro-Rodriguez, and Llamas-Nistal, 2018; Rodrigues, Ramos, Silva, Dourado, and Gomes, 2019) or provided students' considerations for designing dashboards to supporting regulatory processes of learning using multimodal data (Farahmand, Dewan, and Lin, 2020; Jivet et al., 2020; Roberts, Howell, and Seaman, 2017; Rohloff, Sauer, and Meinel, 2019; Schumacher and Ifenthaler, 2018). Some of the dashboard designs used by researchers (Malmberg et al., 2019; Mitri et al., 2017; PijeiraDíaz et al., 2016; Sedrakyan et al., 2020) are in progress based on the theoretical considerations of regulation of learning research and are likely to be simplified in coming years for students and teachers.

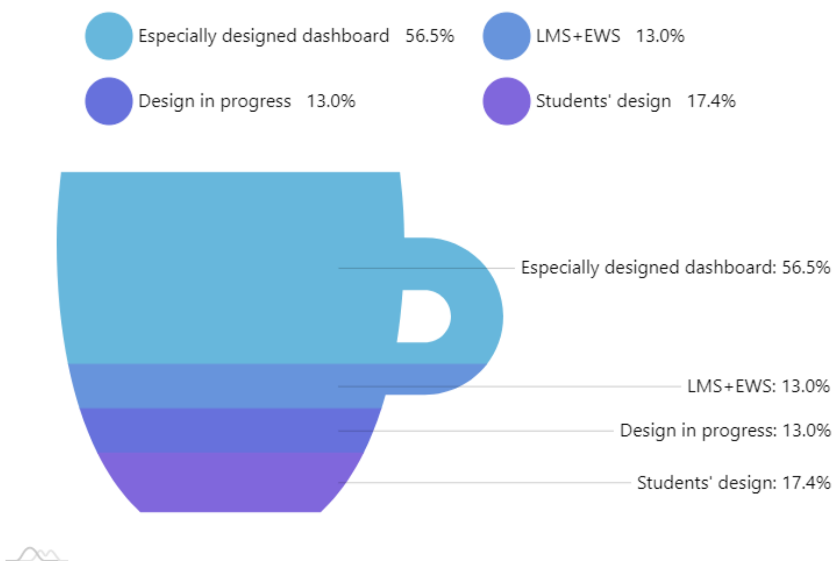

Figure 8.

Instruments used by percentage of studies included in review.

Table 6.

Dashboard instruments used in visualizing SRL/CORL/SSRL

Author of selected studies	Dashboard Instrument	Short description
Groba, Barreiros, Lama, Gewerc, and Mucientes (2015)	SoftLearn	A process mining-based learning analytics tool made from pedagogy and usability testing
Ott, Robins, Haden, and Shephard (2015)	COMP160 laboratory book	Infographic on course demands and performance indicators
Nussbaumer, Hillemann, and Albert (2015)	ComPod	Web based visualization service addressing SRL, psychological, open learner and LA models.
Mitri et al. (2017)	VIT	Visual Inspection Tool (VIT) for supporting researchers in the annotation of multimodal data.
Mejia et al. (2017)	PADA	Web-based tool designed for descriptive visualizations for inspecting reading difficulties.
Tan et al. (2017)	WiREAD	Benefits and drawbacks of a computer-supported collaborative critical reading dashboard
Kuhnel, Seiler, Honal, and Ifenthaler (2018)	MyLA app	HIMATT (Highly Integrated Model Assessment Technology and Tools) instrument.
Pérez-Álvarez, Maldonado-Mahauad, and Pérez-Sanagustin (2018)	NoteMyProgress	A web application that complements a MOOC platform.
Mckenna, Pouska, Moraes, and Folkestad (2019)	U-Behavior	Using photo-elicitation method to prompt learners' reflections
Noroozi et al. (2019)	SLAM-kit	A Graphical User Interface for researchers.
Kia, Teasley, Hatala, Karabenick, and Kay (2020)	LMS integrated with MyLA dashboard	Uses students' performance data, survey data and log data.
Zheng et al. (2021)	HOWARD	Helping Other with Augmentation and Reasoning Dashboard
Aguilar, Karabenick, Teasley, and Baek (2021)	EWS Dashboard	Visualizations of academic performance on SRL strategies.

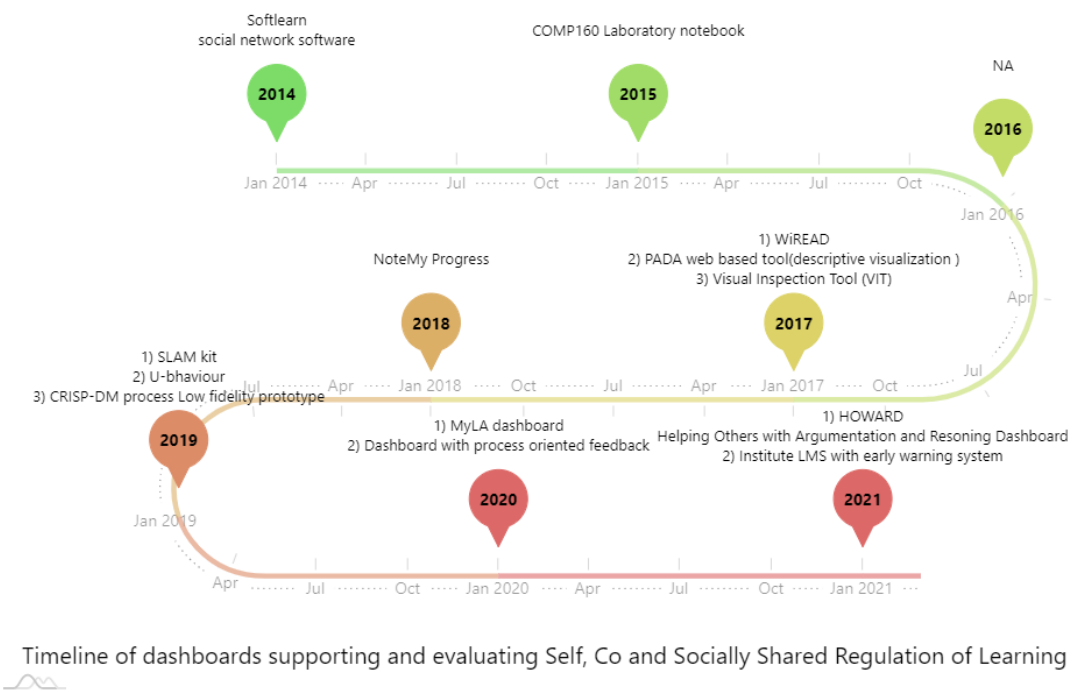

Figure 9.

Dashboard Instruments timeline to visualize SRL, CoRL, SSRL.

Table 6 lists the dashboard instruments used in visualizing SRL/CoRL/SSRL in selected studies in this review with their brief description. Aguilar et al. (2021) used an early warning system dashboard for mentor-mentee meetings to support students’ SRL strategies by focusing on the non-cognitive factors, i.e., students’ academic motivation to learn. With HOWARD, Zheng et al. (2021) provide pedagogical assistance for individuals and groups with separate dashboards for students and teachers. Kia et al. (2020) provided three dashboard views in a student-facing dashboard, MyLA, and identified that dashboard design should be personalized to students’ needs and the context. Noroozi et al. (2019), designed the graphical user interface developed in MATLAB for researchers to visualize group regulation processes using video, audio, and physiological information captured during the learning situation using unobtrusive sensors and cameras. With the U-Behavior tool, Mckenna et al. (2019) facilitated retrieval practice activities to students, creating feedback and critical reflection for both instructors and learners. Pérez-Álvarez et al. (2018), the proposed design of NoteMyProgress tool with two case studies with the design-based research methodology over three Massive Open Online Courses (MOOCs) offered in Coursera points towards the need of designing robust and interactive visualizations. Tan et al. (2017) presented the benefits and drawbacks of dashboard design and pedagogical complexities in considering k-12 learners as a critical stakeholder group in the design process. Mitri et al. (2017) provided a Visual Inspection Tool (VIT) for the annotation of multimodal data, which could be used for learning by providing triangulation of multimodal data, segmentation of time intervals, and downloading annotated datasets. Mejia et al. (2017) designed the PADA dashboard (acronym for the Spanish name Panel de Analíticas de Aprendizajede Dyslexia en Adultos) to identify learners' reading profiles and make their challenges visible to them as feedback. Nussbaumer et al. (2015) provide a web-based service for addressing four components of their conceptual approach: SRL, psychological, open learner, and learning analytics models for visual interaction and feedback. Ott et al. (2015) used the infographic for packaging complex course data into an approachable and engaging format for students using the COMP160 laboratory book. Groba et al. (2015) allow visualization of the learning path of the student graphically using a process mining-based learning analytics tool named SoftLearn.

5.3.2. What Are the Existing Settings of Where and How the Data Has Been Collected, Based on the Reviewed Articles?

Figure 10 Describe the context of the selected studies in the review. The final included studies use different settings, i.e., online, offline, and blended. Most of the studies (n = 12) are carried in an online setting, while four selected studies in the review have used offline settings, and seven have used the blended setting to collect the data and provide feedback to students or teachers. Further for the context, I explored the countries in which these studies were performed. Selected reviewed articles came from different parts of the world, although Europe (Particularly: Finland (n = 3), Germany (n = 3)) and North America (Particularly: USA (n = 4)) are covering most of the selected studies.

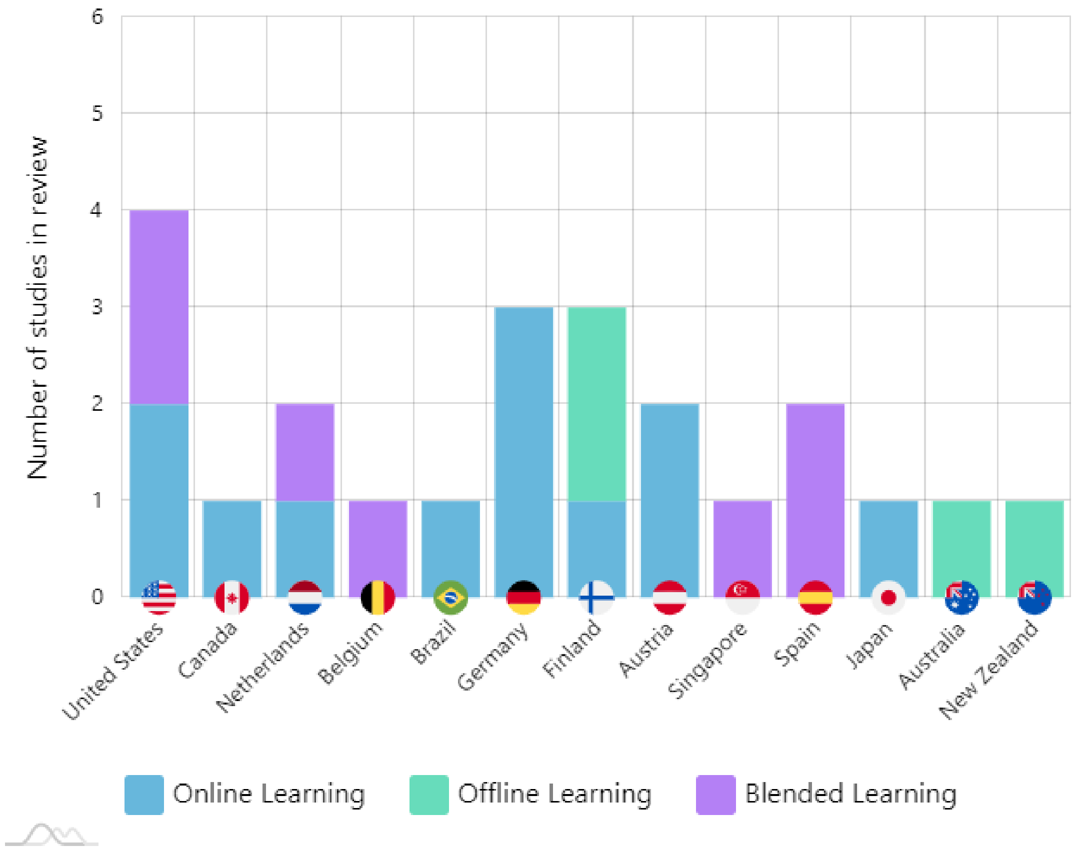

Figure 10.

Settings of where and how the data has been collected.

5.3.3. Who Are the Audiences/ Target Groups of Multimodal Learning Analytics in the Reviewed Articles?

Figure 11 shows the number of studies coming from different countries, which are included in the review. These studies have students, teachers, or researchers as the target audiences. Most of the studies (n = 13) have students as audiences, while some studies are focused on feedback to teachers (n =5) and researcher (n =5).

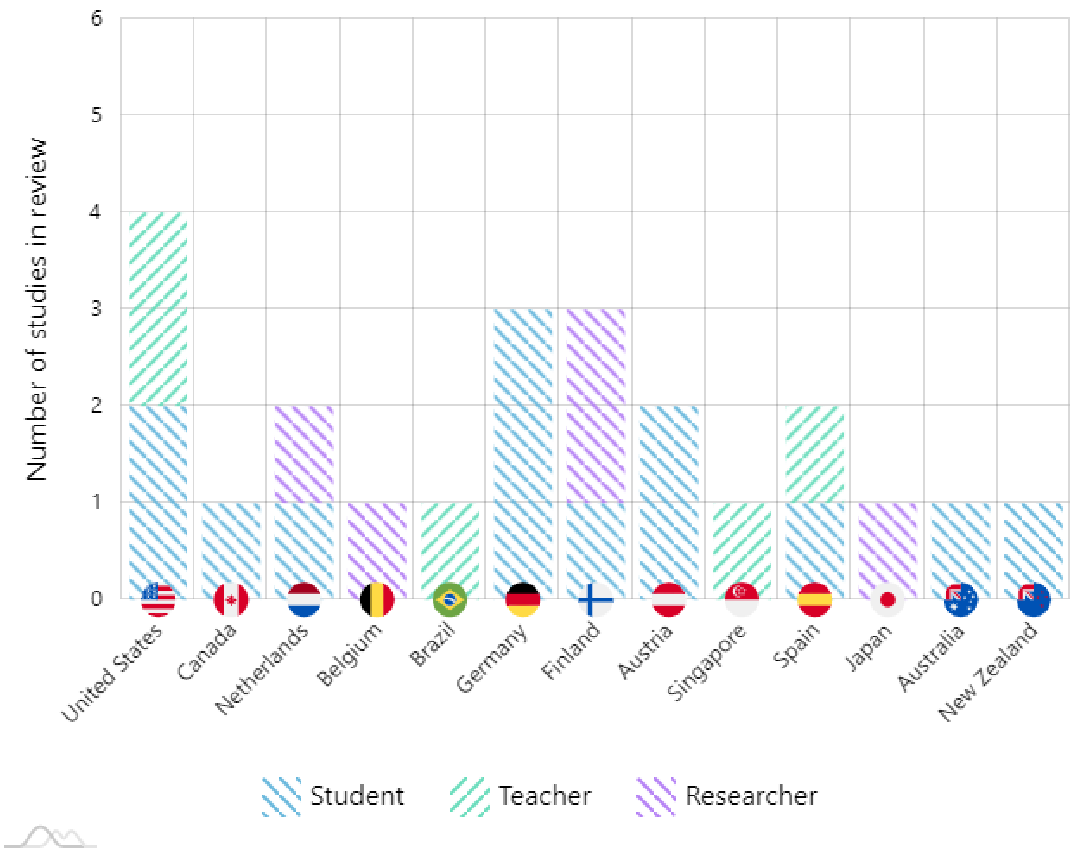

Figure 11.

Audience (target groups) of multimodal learning analytics.

5.3.4. What Constructs Are Used in the Visual Feedback Provided for Students and Teachers?

Most of the studies included in the review have used multiple learning constructs to visualize, such as performance, reflection, cognition, planning, motivation, monitoring, forethought, and emotions. In Figure 12, I have shown which constructs have been more visualized in the selected articles compared with others. It clarifies that the focus of visualization has been students' performance, followed by their reflections, monitoring, and cognition. On the other hand, constructs such as emotion, forethoughts, and students' motivation are used less in the visual feedback provided to students, teachers, or researchers.

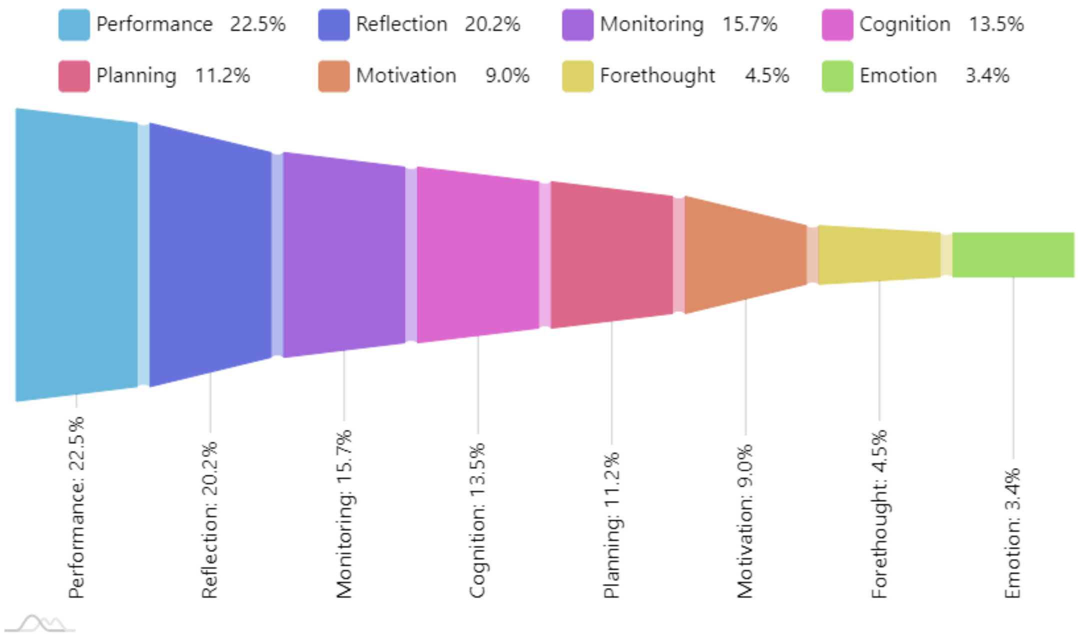

Figure 12.

Constructs used in the visual feedback provided to students, teachers and researchers.

5.3.5. How Does Existing Literature Visualize And/or Measure Different Phases of SRL, CoRL, and SSRL, Using Multimodal Learning Analytics?

In this section, I have identified articles selected in the review based on the type of regulation they have used. For example, are they using Self-Regulated Learning, Co-regulated learning, or Socially Shared regulation of learning? Then further, I have shown the relation of these types of regulation with the targets of regulation such as cognition, motivation, and emotion. After that, these targets relate to 3 main phases of regulations forethought, performance, and reflection (Zimmerman, 2002). Finally, I have checked in the selected papers the types of charts used in the corresponding dashboard to visualize these different phased. It is essential to note that type, target, and phases of regulations are intertwined within an article. Thus one article in the review has used more than one type, target, and phase of regulations. So, with Figure 13, we can see a big picture of used visualizations to support students Self, Co, and Socially Shared regulation of learning. The most used type of regulation in reviewed articles is SRL(n=22), while the CoRL(n=3) and SSRL(n=2) are used in very few numbers. For the target of regulation, cognition and motivation are used more frequently than emotions. Finally, for the phases of regulation, the focus has been on the performance, followed by reflection. In contrast, the forethought phase has been visualized in a few instances. In terms of visualization, Bar Chart (BC), Line Chart (LC), Color Coding (CC), Performance Bar (PB) and Pie Chart (PC) have been used more frequently, followed using Social Network chart (SN), Bubble Diagram (BB), Radar Chart (RC), Heat Maps (HM), the least used visualizations were Stacked Colum Chart (SC), Sankey Diagram (SD) and Histogram (H).

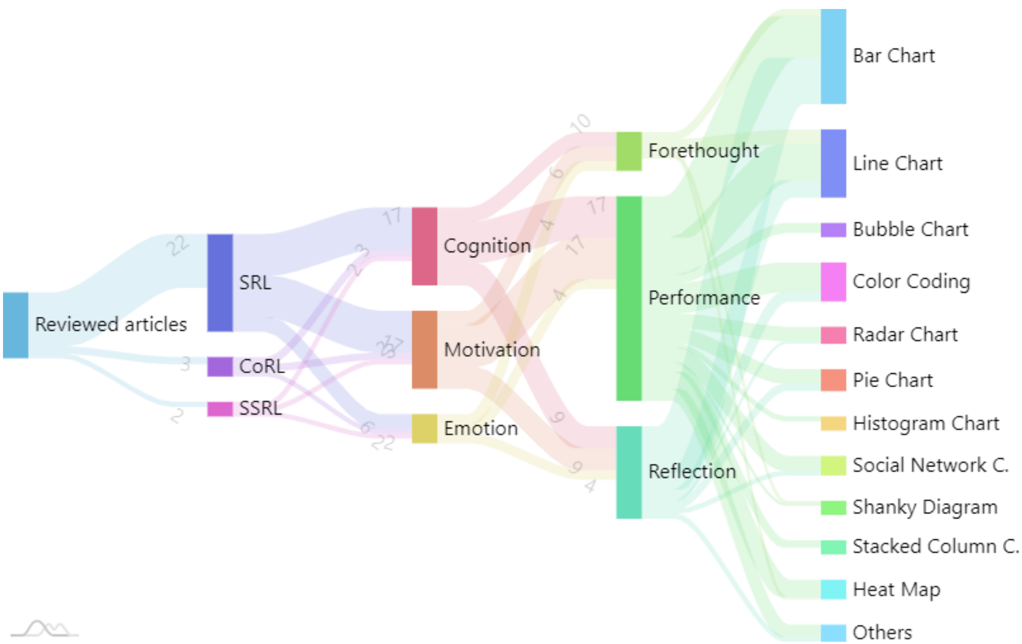

Figure 13.

Targets, phases and types of regulation and visualization methods.

5.3.6. What Multimodal Data Sources Were Used for Providing Information about Different Targets, Phase and Types of Regulation?

Figure 14 shows multimodal datasets used in selected articles for providing information about students' different layers of the regulation process. Most studies used survey data/ questionnaires designed for identifying regulatory processes during learning. It has followed using Log data, performance data(i.e., exam results), LMS with EWS designed to provide monitoring opportunities to the learners. Different sensors data, learning diaries, think aloud screen capture are used less. The least used data modalities were eye tracking and Facial expression for detecting emotions.

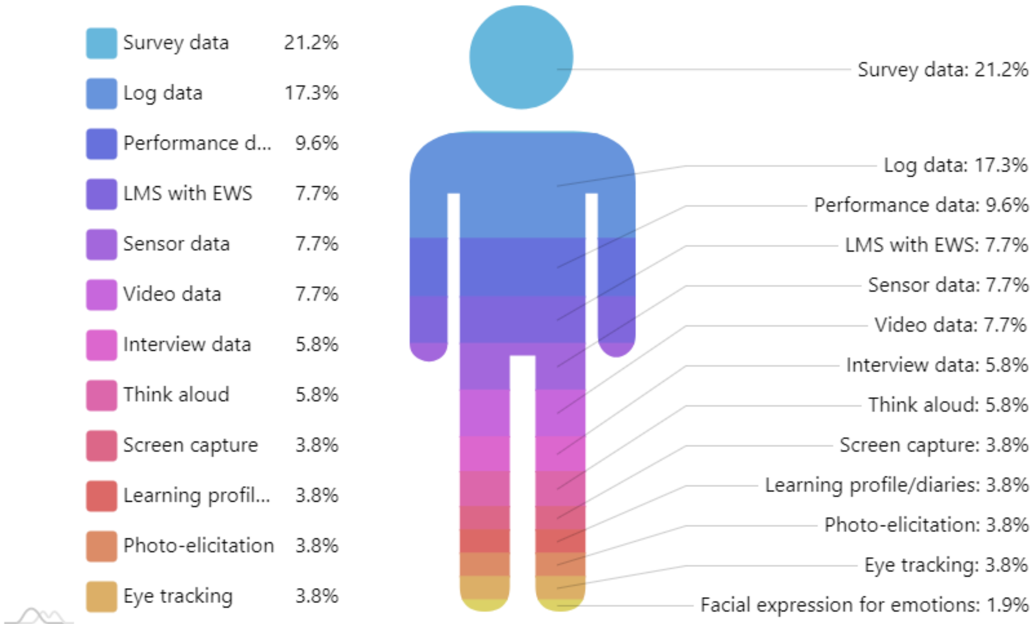

Figure 14.

Multimodal data types used for visualizing students' regulation process.

6. Discussion

The aim was to identify how visualization techniques have assisted researchers, teachers, and students understand different targets and phases of regulation using multimodal data in recent studies. For this, the review collected existing research-based instruments designed to measure and visualize Self, Co, and socially shared regulation of learning and engagement of learners. The review included 23 papers out of 386 papers retrieved from 5 different databases at the interaction of multimodal learning analytics, regulation theories of learning, and visual analytics literature of the last decade (2011-2021). First, I distill settings, instruments, contexts, and audiences; second, I explore the integration of theoretical groundings of Self, Co, and Socially Shared regulation of learning research and the promise of multimodal analytical approaches to visualize learning. In the following subsections, I discuss and synthesize the finding around review questions. This section provides a general interpretation of the results in the context of other evidence.

6.1. RQ 1 Instruments, Settings, Constructs and Audiences

Most of the identified dashboard instruments in the review are in their development phases. They provide the considerations to design the dashboards for students and teachers in different online, offline, or blended settings. The focus on online data collection is understandable, considering that most of these dashboards were designed to collect students' trace data. However, some studies identified in this review focus more on surrounding data using different sensors in natural classroom settings (Malmberg et al., 2019; Mitri et al., 2017; Noroozi et al., 2019; PijeiraDíaz et al., 2016; Sedrakyan et al., 2020). Through this development phase, it has been established that students' learning processes are moving towards more explainable dashboards for students and teachers (Farahmand et al., 2020; Jivet et al., 2020; Roberts et al., 2017; Schumacher and Ifenthaler, 2018). These dashboards are using more than objective data and self-repots in face-to-face classroom setups and online learning environments.

These dashboards will further address researchers' concerns on relying only on self-reports as they are obtrusive yet popular because of their reliability and validity used in traditional education research (Roth et al.,2016). However, Winne (2019) points that in self-reports, learners overestimate their responses and fail to capture their actual study behaviors. This review was important to see how dashboard instruments are designed and used as per the regulation models and theories. In this review, the identified studies rely on regulation theories to help us define what can count as information and thus help us reduce the complexity of regulation processes. It was surprising that out of 23 selected articles, only two articles (Malmberg et al., 2019; Noroozi et al., 2019) shared the same instrument. One reason for this could be the novelty of this field of research. Nonetheless, building on these instruments will help researchers develop suitable changes in these instruments to visualize Self, Co, and Socially Shared regulatory processes.

Most of the selected studies in this review have university students as participants. Only a few studies (Malmberg et al., 2019; PijeiraDíaz et al., 2016; Tan et al., 2017) are from K-12 settings, while no study addressed the workplace learning settings. These findings shed light on the need of future research in K-12 and workplace settings for generalizable guidelines. Here the main challenge is to use simplified visualization techniques for K-12 students to support their regulatory processes. Therefore, researchers need to work more closely with teachers and students to identify the markers and their visualization techniques for meaningful feedback. We need to work on creative approaches such as layered storytelling for making insight from data (Martinez-Maldonado et al., 2020). Also, in terms of audiences, the designed dashboard instruments focus on impact and student use, while some are used specifically for researchers to advance our basic scientific understanding of learning. This equity issue at the level of audiences needs to be considered for future studies.

From the selected articles in the review, it is clear that very few studies addressed collaborative learning settings (n = 3/23). Most studies focused on individual learning and the performance of students. One of the reasons for this is the complexity collaborative learning presents in the investigation than individual learning (Winne, 2010). This complexity makes the visualization of learning more difficult using traditional visualization techniques. Nevertheless, it can be noted from this review that dashboard design and use of multimodal learning analytics has advanced the traditional methods which relied on learners' subjective measures of their SRL skills. Now, offline data is increasing to match the online measures, such as the use of log data collected from institutes' learning management systems. These findings from the review provide noticeable evidence to point to the shift from using SRL/SSRL/CoRL measurement tools to provide support for students' regulatory skills.

The visualized constructs in regulation research provide us with more markers for understanding the complex process of regulation of cognition, motivation, and emotion. The number of articles included in the review pointed to the focus on performance monitoring of students. On the other hand, using multiple data channels for identifying emotion and forethought processes was limited (Rohloff et al., 2019; Zheng et al., 2021). Future empirical studies must address the complex process of emotions. In this regard, multimodal approaches in regulation research can help, as it provides room for multiple data channels in drawing more valid and reliable inferences about the learning processes.It is essential to keep in mind that there is more going on in learner's minds than their actions reveal.

6.2. RQ 2 Targets, Phases and Types of Regulation: Data Sources and Visualization Methods.

The review examines how researchers combine visualization, multimodal analytics, and regulation theories to understand students' learning process and thus to support them in improving their regulatory skills. I found that relatively few articles, only 23 studies met the criteria for this review. Furthermore, even fewer articles were explicit, either procedurally or theoretically, about how visualization supports students' improving their regulatory skills. Based on this review, this would be fair to say that, until now, research connecting the multimodal data visualization and theoretical grounding of regulation is limited. Nevertheless, researchers focus on objective data is bringing more visualization techniques for multivariant constructs such as motivation, emotions and metacognition (Jivet et al., 2020; Kia et al., 2020; Noroozi et al., 2019; Zheng et al., 2021).

I have observed specific, clear trends in visualizing Self, Co, and Socially Shared Regulation of Learning from the review process. In terms of targets of regulation, cognition and motivation are used extensively in visualizations. While the regulation phase is mainly focused on the students' performance, followed by students' reflections. The forethought and Emotion phase are visualized the least and only used basic visualization such as bar charts/progress bars and line charts. Here, it is important to consider the role, motivation, and emotion in SRL (Boekaerts and Pekrun, 2015; Zimmerman, 2002) by influencing metacognitive processes, executive cognitive functions, and learning results (Boekaerts and Pekrun, 2015; Pintrich, 1990). For instance, students' self-efficacy beliefs can influence their will to engage in cognitive functions and, thus, contribute to their learning achievements (Pintrich, 1990). Emotions also have different effects on student learning. Positive emotions can promote flexible and creative problem solving, whereas negative emotions promote more rigid, detail-oriented, and analytical ways of thinking (Boekaerts and Pekrun, 2015). Despite this established body of research, the results of this study indicate that emotional learning aspects are notably lacking in the instruments designed to support students' regulatory skills. Only one study included in the review (Zheng et al., 2021) worked explicitly on visualizing the emotional aspects of learning.

The most visualized phase of the regulation in the learning process was performance. A significant number of publications also focused on visualizing students' reflections. This inclination to performance inherently points towards our understanding of learning, which is performance-oriented. However, to get a holistic understanding of learning, we need to focus on less represented targets such as emotions and less visualized phases such as forethought and motivation. On the one hand, this finding is in line with the previous empirical evidence showing that learners improve their cognition with proper monitoring of their performance (Costa, Sanches, Amorim, do Nascimento Salvador, and dos Santos Souza, 2020; Jivet et al., 2021; Sharma and Giannakos, 2020), indicating the need to provide performance visualizations. On the other hand, over the years number of empirical research has also exposed the importance of students' motivation and emotions during the learning process (Azevedo et al., 2017; Dindar et al., 2020; Munshi et al., 2020; Noroozi et al., 2020). This is one of the future research directions to explore how motivation and emotional supports could be given to students with optimal visualizations.

As results in RQ1 and RQ2 showed, instruments focused on performance and the use of basic visualization methods need to be explored in detail. Researchers need to collaborate more with information visualization experts to use the full potential of visual feedback (Vieira et al., 2018). I offer three hypotheses to explore why researchers focused on performance indicators. Firstly, performance measures are easier to capture in traditional learning environments. Secondly, they provide alignment with the curriculum to both students and teachers. Finally, they are not so reliant on objective data as also pointed by Noroozi et al. (2020). These hypotheses direct us towards future research in the field of regulation research. From the review, the SRL/SSRL/CoRL visualization approaches can be categorized into two. The first category is approaching that extends students' performance based on data-driven and personalized support to learners. The second is to understand the theoretical grounding of regulation inclusion of missing phases and targets of regulation in visual to students. It is to say; we need more work on metacognitive feedback reflecting by stopping learners from reflecting but also using objective measures on the learning process. Both approaches require teachers' knowledge and explanation from the analyzed data and visualization presented. Most of the studies included in the review focus on the first model, while the second model calls for more work.

Finally, this review suggests that continuous development of instruments and research at the intersection of multimodal learning analytics and regulation theories is essential for developing instruments to make the visible regulatory processes more focused on visualizing motivational and emotional processes of learning. Also, there is a need to focus on the collaborative aspect of regulation, as making the targets and phases of regulation visible is essential for successful group work (Malmberg et al., 2019; Martinez-Maldonado et al., 2021; Noroozi et al., 2019). The reasoning behind this finding could be that the feedback given to students is only supportive if students can interpret their data concerning their peers and make strategic change timely in their learning strategies accordingly. Winne (2018) pointed out that learners are experimenting when they engage in the regulation process. Supporting students in their experimentation by providing them meaningful data about why their strategies are failing or succeeding is essential for their learning process. Furthermore, Panadero, Tapia, and Huertas (2012) pointed out rubrics and self-assessment scripts for the successful and unsuccessful set of regulatory strategies. These recommendations allow us to move towards designing regulatory learning processes and promote students' agency, meaning that learners become "masters of their own learning" (Zimmerman, 1990, p. 4).We need to provide instruments to build and organize their knowledge and make them strategic about their learning processes.

6.3. Practical Implications

A few implications of this review are; first, the analyses revealed that the most under-explored topic in the visualization of regulatory processes of learning is emotions and forethought, despite its wide recognition as essential for the regulation of learning. It is necessary to develop more instruments to support these constructs and redesign instruments based on all phases and targets of regulation. Researchers need to work on emotion visualization using multivariate visualization techniques, which is not frequent in current instruments. Second, the visualization used in selected articles is limited to basic charts and color-coding. These visualizations require the use of multivariate visualization techniques to visualize complex dimensionality of learning. Finally, the limited use of dataset in identifying regulatory processes need more work on sensors and facial expression detection software to provide the necessary process data for meaningful interpretation. These implications will help researchers design dashboards to provide timely feedback on students' learning strategies and thus improve students' regulatory skills.

6.4. Direction for Future Research

Present-day technologies enable process-oriented research. In addition, physiological data can be measured for the whole process, making it different from the traditional data collection. These multimodal data channels, which match the theoretical understanding of learning, are evolving along with our understanding of multidimensional learning phenomena, e.g., cognition, motivation, emotion, and social processes. At the same time, these new data collection methods could help us update theories about learning and interaction. Therefore, the visualization instruments and studies presented in this review can help teachers in their practice and help us as researchers see some unseen patterns in learning and interactions in the future.

Further, due to the COVID-19 situation, students' online presence continuously supplies a massive dataset. Fitting such a dataset on ethical, practical, and methodological dimensions is not an easy task and requires researched-backed policy formulation. The backup of decade-long research and discussions has provided a solid grounding for further research in this area. Such research further guides us towards solid theoretical grounding to filter relevant data from the messy multimodal datasets. It will help conduct the data gathering, pre-processing, analysis, annotation, and sense-making. It is important to remember that this data should be meaningful not only for learning scientists but also for other stakeholders (students, teachers, or parents). Moreover, it makes progress toward mapping and developing learning analytics for nested models of regulated learning, which is difficult to attain using conventional education research methods.

Saqr and Wasson (s.a.) pointed towards the need for research on the social aspect of the COVID-19 pandemic to foster engagement, trust, and adaptive education. There are three main challenges, which we need to address as a community: ethical, practical, and methodological. These challenges require more collaboration between different stakeholders, i.e., researchers from multiple disciplines, teachers, students, policymakers, and parents. Nevertheless, any further synthesis of such a diverse group is not available as the field of Learning Analytics is yet in its developing phase. This review reflects the diligence of researchers in developing regulation theory-backed instruments for the visualization of different targets and phases of regulated learning. I regard the directions as mentioned above of research for future undertakings.

6.5. Limitations and Reporting Biases

In completing a review with such multifaceted constructs, limitations are inevitable. The principal limitations of the evidence included, along with the limitations of this review process, are in this section. This section also presents assessments of the risk of bias due to missing results (arising from reporting biases) for each synthesis assessed and addressing the study risk of bias assessment.

The first concerns how I bounded the search to conduct the review. Through the specific focus on the regulation of learning in an education context, I have potentially excluded studies that examine learning using other theoretical backgrounds than Self, Co, and Socially Shared Regulation of Learning. I chose to narrow the theoretical focus for two reasons. Regulation theories give agency to learners, so they are in control of their data. This agency is significant in the light of data ethics (Gasevic, Dawson, and Jovanovic, 2016). Secondly, I focused on multimodal analytics and visualization at once. This dual focus could potentially confound my particular interest in how connections between multimodal analytics and visualization are warranted.

Additionally, I set the parameter on students and teachers in order to consider classroom practices. Practically speaking, this parameter led identification of a manageable body of literature. As "regulation of learning" in the context of multimodal data has been used in many different pieces of literature outside education settings, i.e., in self-driving cars.

Another limitation could be the use of only six databases with studies published in English only. Even though I have selected these based on the most widely used databases, involving relevant conference proceedings and journals related to the concerned field of research, nonetheless, consideration of others could have resulted in the inclusion of additional material. Finally, it should be emphasized that this study did not synthesize results from selected studies to determine the average impact of visualizing SRL, CORL, and SSRL on students' learning. That is to say, it does not provide a meta-analysis. Hence, the results do not reveal the effectiveness of the instruments used in the selected studies. I avoided it based on two reasons. First, the limited number of articles in the review was not sufficient for making any effective comparison. Second, in this master's thesis, data extraction is done by a single author. Therefore, defining selected studies' different levels of granularity could be rightly questioned. As such process of coding does not provide reliability indices (e.g., Cohen Kappa). Here, involving one more researcher could provide a degree of reliability for the consistency of coding. This situation presents a detection bias due to the possibility of misinterpretation of identified evidence coming from a particular study.

7. Conclusions

The regulation of learning occurs at different targets, phases, and types of regulation embedded in one another. The growing importance of collaborative research and the use of multimodal datasets on learning processes are increasingly recognized. Still, it requires attention on how we visualize regulatory aspects of learning to students and teachers? This thesis has conducted a systematic review to identify instruments to visualize regulation of learning, which points that the future lines of research should not focus exclusively on SRL but include SSRL and CoRL as theoretical grounding in their research. Social regulation research is essential as they provide the aspects of groups' learning characteristics to students, so teams regulate their collaborative learning. Such instruments' design requires the expertise of technological know-how and deep engagement in social and cultural characteristics of learning research. Bransen et al. (2021) suggest researchers shift their focus from how to optimize learning to the broader perspective of how to most effectively unravel the levels of self-, co-, and socially shared regulation of learning.

In conclusion, this thesis highlights studies at the intersection of SRL/SSRL/CoRL, multimodal learning analytics, and visual analytics by paying particular attention to two RQs. To address the first RQ, I distilled instruments, settings, constructs, and audiences. I reported the following key results from the review: (1a) identified 12 dashboard instruments used to visualize Self, Co, and Socially Shared Regulation of learning between 2014-2021. (1b) The audience in selected studies mainly were both students and teachers. (1c) Online learning has been explored the most in terms of settings, followed by blended learning and offline learning. (1d) The constructs used in visual feedback provided for students and teachers are mainly focused on performance followed by reflection and monitoring. At the same time, forethought and emotions are the most minor visualized constructs in the feedback.

To address the second RQ, I identified targets, phases, and types of regulation and their visualization methods along the multimodal data sources used in the studies. I reported the following key results from the review: (2a) studies mainly used theoretical grounding of SRL CoRL, and SSRL are used significantly less. Research studies are focused mainly on visualizing cognition and motivation as targets and performance as a phase of regulation. In contrast, emotions as target and reflection and forethoughts as phase are less visualized in the current instruments. In terms of visualizations, bar charts, line charts, color coding, progress bars have been used more frequently than bubble charts, stacked column charts, funnel charts, heat maps, and Sankey diagrams, representing multidimensional data. (2b) In terms of data sets survey data, log data are used most frequently, followed by sensors and video data, while the eye tracking data and facial expression detection were used very less.

Although the number of articles in the review is low considering the novelty of the field of research, they cover different types, targets, phases, and types of regulation research. There is still a long road ahead to visualize regulation of learning and provide feedback to students on how to change their strategies with timely feedback during individual and collaborative learning situations. The thesis also highlights the need for research in the intersection of multimodal learning analytics, regulation theories of learning, and visual analytics. Mainly, focus on qualitative work on designing learning dashboards are essential for its adaption in classrooms. Therefore, the conclusions here should be put into the context of future studies to come. The conclusions here intend to spark thoughts about utilizing multimodal data to visualize learning while enriching and advancing research on SRL, CoRL, and SSRL. Multimodal learning analytics, regulation theories, and visualization will play a significant role in LDAs' design in the future. As with the arrival of the Internet of Things (IoT), it would be easier to collect more information about an individual and group and thus to provide effective, efficient, and understandable visualization of learning processes.

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8. Appendices

Appendix 1	Reference list with data of all analyzed articles in this review
Appendix 2	PRISMA 2020 Checklist

Table 7. *Reference list with data of all analyzed articles in this review (continue..)*

Authors	Reference study	Year	Country	Learning Setting	Main Audience	Regulation			Data Sources	Visualization used
						Type	Target	Phase		
Aguilar et al. (2021)	Associations between learning analytics dashboard exposure and motivation and self-regulated learning.	2021	USA	Blended	Student	SRL	Motivation	Performance	LMS with EWS,log files, pre and post survey (PALS, SRLQ)	Dashboard used bar chart, line chart and tables, performance status (Color coding i.e., green, yellow, or red).
Zheng et al. (2021)	Self-regulation and emotion matter: A case study of instructor interactions with a learning analytics dashboard.	2021	USA	Online	Teachers	SRL	Emotion	Forethought, Reflection	Screen capture and think aloud	Dot plot, social network analysis, activity view chart
Kia et al. (2020)	How Patterns of Students Dashboard Use Are Related to Their Achievement and Self-Regulatory Engagement	2020	USA	Blended	Students	SRL	Cognition	Performance data	Performance data, survey data(MSLQ), usage data (log)	Including line graphs, bar charts, gauges, dials, heat maps,and more
Farahmand et al. (2020)	Student-Facing Educational Dashboard Design for Online Learners	2020	Canada	Online	Students	SRL	Cognition and Motivation	Planning, Monitoring	NA	NA

Table 7. *Reference list with data of all analyzed articles in this review (continue..)*

Authors	Reference study	Year	Country	Learning Setting	Main Audience	Regulation Type	Regulation Target	Regulation Phase	Data Sources	Visualization used
Jivet et al. (2020)	From students with love: An empirical study on learner goals, self-regulated learning and sense-making of learning analytics in higher education.	2020	The Netherlands	Online	Students	SRL	Cognition and Motivation	Performance, reflection	Survey OSL-Q questionnaire Dashboard mock-up	line and dot plots, bar chart
Sedrakyan et al. (2020)	Linking learning behavior analytics and learning science concepts: Designing a learning analytics dashboard for feedback to support learning regulation.	2020	Belgium, Finland	Blended	Researchers	SRL, CoRL	Cognitive, Motivation and Emotions	Planning, Monitoring	Learning process data: planning, monitoring and adaption profile	spider graphs, barchart, area chart, line graph, heat map, social network analysis
Rodrigues et al. (2019)	Forecasting Students' Performance Through Self-Regulated Learning Behavioral Analysis.	2019	Brazil	Online	Teachers	SRL	Performance	Monitoring	LMS moodle data, student performance data	ROC graph. coloured bubble chart, bar chart, line graph
Rohloff et al. (2019)	Student Perception of a Learner Dashboard in MOOCs to Encourage Self-Regulated Learning	2019	Germany	Online	Students	SRL	Motivation, Emotion	Performance	Survey (Dashboard HPI mooc, SRL skills)	bar chart, heat map, line chart

Table 7. *Reference list with data of all analyzed articles in this review (continue..)*

Authors	Reference study	Year	Country	Learning Setting	Main Audience	Regulation			Data Sources	Visualization used
						Type	Target	Phase		
Noroozi et al. (2019)	Multimodal data to design visual learning analytics for understanding regulation of learning.	2019	Finland, The Netherlands	Blended	Researchers	SRL, CoRL	Cognition, Motivation and Emotions	Forethought, performance and reflection	Video data, sensor data points, and log data	Line graph, dot plot and bar charts
Mckenna et al. (2019)	Visual-Form Learning Analytics: A Tool for Critical Reflection and Feedback	2019	USA	Online	Teacher	SRL	Cognition	Performance	Survey data, student performance data, photo-elicitation response	NA
Malmberg et al. (2019)	Going beyond what is visible: What multichannel data can reveal about interaction in the context of collaborative learning?	2019	Finland	Offline	Researchers	SRL, SSRL, CoRL	Motivation, emotion, cognition	Forethought, performance and reflection	Physiological data,video observations, and facial recognition data	NA
Pérez-Álvarez et al. (2018)	Design of a Tool to Support Self-Regulated Learning Strategies in MOOCs	2018	Austria	Online	Students	SRL	Cognition (performance data), motivation	performance, reflection	Log data (Evaluation phase, Enactment phase, adoption phase)	bar chart, line graph, non interactive

Table 7. *Reference list with data of all analyzed articles in this review (continue..)*

Authors	Reference study	Year	Country	Learning Setting	Main Audience	Regulation			Data Sources	Visualization used
						Type	Target	Phase		
Schumacher and Ifenthaler (2018)	Features students really expect from learning analytics.	2018	Germany	Online	Students	SRL	Motivation	Performance	Survey, dashboard, oral interviews	Heat Map, tables, color coding
Kuhnel et al. (2018)	Mobile Learning Analytics in Higher Education: Usability Testing and Evaluation of an App Prototype	2018	Germany, Austria	Online	Students	SRL	Cognition and motivation	Forethought	survey, eye tracking	Dashboard design web application
Kuhnel et al. (2018)	Mobile Learning Analytics in Higher Education: Usability Testing and Evaluation of an App Prototype	2018	Germany, Austria	Online	Students	SRL	Cognition and motivation	performance	Survey, eye tracking	Text based Dashboard design web application
Tan et al. (2017)	Learner Dashboards a Double-Edged Sword? Students' Sense-Making of a Collaborative Critical Reading and Learning Analytics Environment for Fostering 21st-Century Literacies	2017	Singapore	Blended	Teachers	SRL	Cognition and motivation	performance, reflection	Survey and interviews, performance data	Spider web, bar chart, social network map, social network analytics

Table 7. *Reference list with data of all analyzed articles in this review (continue..)*

Authors	Reference study	Year	Country	Learning Setting	Main Audience	Regulation			Data Sources	Visualization used
						Type	Target	Phase		
Mejia et al. (2017)	A Novel Web-Based Approach for Visualization and Inspection of Reading Difficulties on University Students	2017	Spain	Blended	students	SRL	Cognitive, motivational	Performance	Survey, sensors, log data for activity based engagement	bar-charts, line-charts, and pie-charts
Li et al. (2017)	Using Learning Analytics to Support Computer-Assisted Language Learning	2017	Japan	Online	Researchers	SRL	Cognitive and motivation	performance, reflection	Log data(access log, completion log and answer log), test scores	line chart (learning progress) each student wrt to class average, heat map to show high and low scores in test during the process of learning.
Roberts et al. (2017)	Give Me a Customizable Dashboard: Personalized Learning Analytics Dashboards in Higher Education	2017	Australia	Offline	Students	SRL	NA	NA	content analysis of student's drawing of dashboard,audio data, survey	NA

Table 7. *Reference list with data of all analyzed articles in this review (continue..)*

Authors	Reference study	Year	Country	Learning Setting	Main Audience	Regulation			Data Sources	Visualization used
						Type	Target	Phase		
Mitri et al. (2017)	Learning Pulse: A Machine Learning Approach for Predicting Performance in Self-Regulated Learning Using Multimodal Data	2017	The Netherlands	Offline	Researchers	SRL	Cognition, motivation and emotions	Forethought, performance and reflection	Bio sensors, log file, sensor data, performance indicator (stress, productivity, challenges and abilities)	scatter plot for flow, line plot for working hours for reading, writing, meeting, communication and other
PijeiraDíaz et al. (2016)	Investigating Collaborative Learning Success with Physiological Coupling Indices Based on Electrodermal Activity	2016	Finland	Offline	Researchers	SRL	Cognition, motivation and emotions	Performance and reflection	MSLQ questionnaires, videotaping, activity logs, wrist band biosensors, eye tracking	NA
Nussbaumer et al. (2015)	A Competence-Based Service for Supporting Self-Regulated Learning in Virtual Environments	2015	Austria	Online	Students	SRL	Cognition, motivation	Performance	Survey data, student performance data, test evaluation	line chart , social network for navigation behaviour

Table 7. *Reference list with data of all analyzed articles in this review (continue..)*

Authors	Reference study	Year	Country	Learning Setting	Main Audience	Regulation			Data Sources	Visualization used
						Type	Target	Phase		
Ott et al. (2015)	Illustrating Performance Indicators and Course Characteristics to Support Students' Self-Regulated Learning in CS1	2015	New Zeland	Offline	Students	SRL	Cognition	Performance	login data, exam score , interview, think aloud	Infographics, pie chart, line graph, markers and tags
Groba et al. (2015)	Using a learning analytics tool for evaluation in self-regulated learning	2014	Spain	Online	Teachers	SRL	Cognition and motivation	performance	Screen activities, learning dairies, social network	D/F-graphs

Table 8. *PRISMA 2020 Main Checklist*

Topic	No.	Item	Location where item is reported
TITLE			
Title	1	Identify the report as a systematic review.	Title page
ABSTRACT			
Abstract	2	As per PRISMA 2020 checklist	Page 2
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of existing knowledge.	Section 2, Page 19
Objectives	4	Provide an explicit statement of the objective(s) or question(s) the review addresses.	Section 3, Page 23
METHODS			
Eligibility Criteria	5	Specify the inclusion and exclusion criteria for the review and how studies were grouped for the syntheses.	Section 4.2, Page 30
Information Sources	6	Specify all databases, registers, websites, organisations, reference lists and other sources searched or consulted to identify studies. Specify the date when each source was last searched or consulted.	Section 4.1.1, Page 27
Search strategy	7	Present the full search strategies for all databases, registers and websites, including any filters and limits used.	Section 4.1.2, Page 28

Table 8. *PRISMA 2020 Main Checklist (Cont.)*

Selection Process	8	Specify the methods used to decide whether a study met the inclusion criteria of the review, including how many reviewers screened each record and each report retrieved, whether they worked independently, and if applicable, details of automation tools used in the process.	Section 4.3, Page 32
Data Collection Process	9	Specify the methods used to collect data from reports, including how many reviewers collected data from each report, whether they worked independently, any processes for obtaining or confirming data from study investigators, and if applicable, details of automation tools used in the process.	Section 4.3.2, Page 33
Data Items	10a	List and define all outcomes for which data were sought. Specify whether all results that were compatible with each outcome domain in each study were sought (e.g. for all measures, time points, analyses), and if not, the methods used to decide which results to collect.	Section 4.3.2, Page 33

Table 8. *PRISMA 2020 Main Checklist (Cont.)*

	10b	List and define all other variables for which data were sought (e.g. participant and intervention characteristics, funding sources). Describe any assumptions made about any missing or unclear information.	Section 4.3.2, Page 33
Study risk of bias assessment	11	Specify the methods used to assess risk of bias in the included studies, including details of the tool(s) used, how many reviewers assessed each study and whether they worked independently, and if applicable, details of automation tools used in the process.	Section 6.5, Page 54
Effect measures and Synthesis methods for Meta Analysis	13-15	Describe the processes used for Meta Analysis, reporting Bias and certainty assessment, risk ration and mean difference.	Not conducted
RESULTS			
Study Selection	16a	Describe the results of the search and selection process, from the number of records identified in the search to the number of studies included in the review, ideally using a flow diagram.	Section 5.1, Page 34
	16b	Cite studies that might appear to meet the inclusion criteria, but which were excluded, and explain why they were excluded.	Section 5.1, Page 34

Table 8. *PRISMA 2020 Main Checklist (Cont.)*

Study Characteristics	17	Cite each included study and present its characteristics.	Section 5.1, Page 35
Risk of bias in studies	18	Present assessments of risk of bias for each included study.	NP
Results of individual studies	19	For all outcomes, present, for each study: (a) summary statistics for each group (where appropriate) and (b) an effect estimate and its precision (e.g. confidence/credible interval), ideally using structured tables or plots.	Section 5.1, Page 35-36
Results of synthesis	20a	For each synthesis, briefly summarise the characteristics and risk of bias among contributing studies.	Section 5.1, Page 36-44
	20b	Present results of all statistical syntheses conducted. If meta-analysis was done, present for each the summary estimate and its precision (e.g. confidence/credible interval) and measures of statistical heterogeneity. If comparing groups, describe the direction of the effect.	Section 5.1, Page 36-44
	20c	Present results of all investigations of possible causes of heterogeneity among study results.	Section 5.1, Page 36-44

Table 8. *PRISMA 2020 Main Checklist (Cont.)*

	20d	Present results of all sensitivity analyses conducted to assess the robustness of the synthesized results.	Section 5.1, Page 36-44
Reporting biases	21	Present assessments of risk of bias due to missing results (arising from reporting biases) for each synthesis assessed.	Section 6.5, Page 54
Certainty of evidence	22	Present assessments of certainty (or confidence) in the body of evidence for each outcome assessed.	NP
DISCUSSION			
Discussion	23a	Provide a general interpretation of the results in the context of other evidence.	Section 6.1, Page 47
	23b	Discuss any limitations of the evidence included in the review.	Section 6.5, Page 54
	23c	Discuss any limitations of the review processes used.	Section 6.5, Page 54
	23d	Discuss implications of the results for practice, policy, and future research.	Section 6.4-6.5, Page 52-53

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